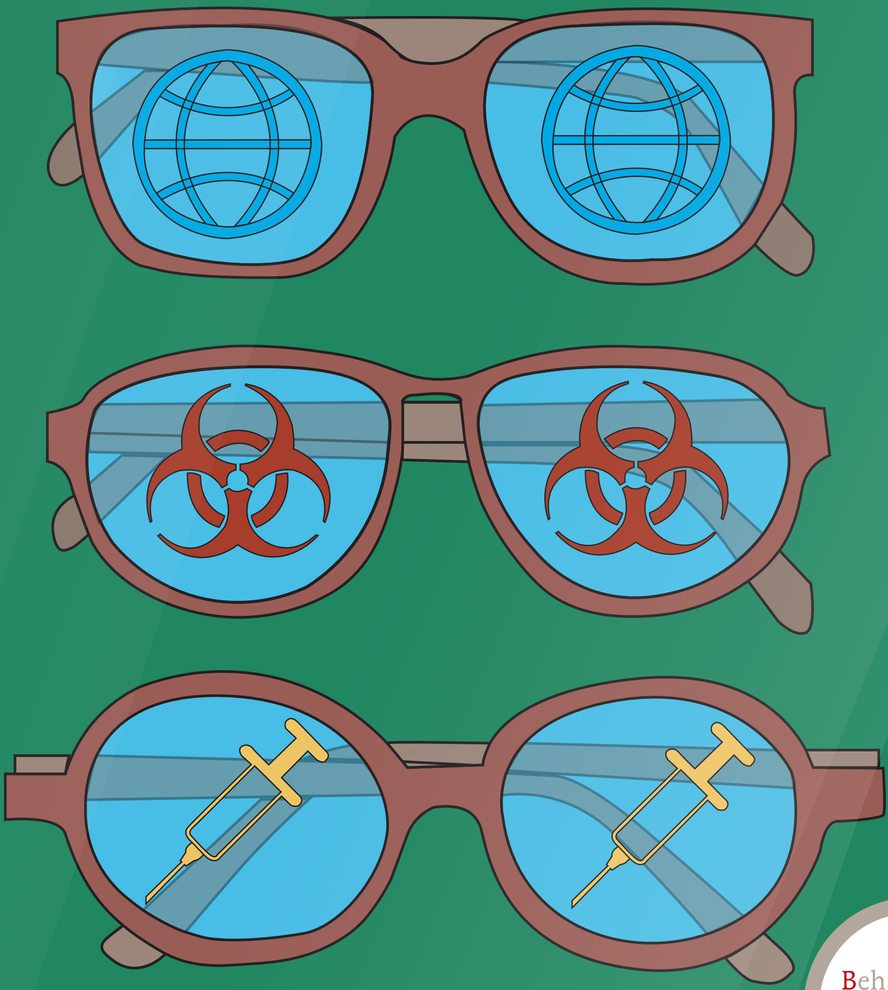
CORRECTING MISPERCEPTIONS ABOUT CONTESTED TOPICS THROUGH SCIENCE COMMUNICATION

Aart van Stekelenburg



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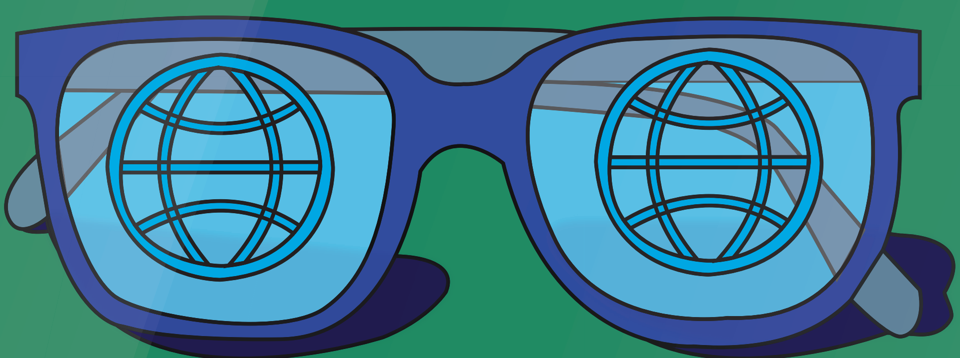
Reading Guide

The public does not agree about the facts surrounding a number of formidable challenges that the world is facing. Science communication plays an important role in informing people about the facts related to such important societal topics, but it is not always effective. The aim of this dissertation is to investigate how people stick to false beliefs in the face of corrective information and how science communication can improve to help people come to scientifically accurate beliefs.

This dissertation consists of five chapters. Chapter 1 provides a general introduction to and discussion of the work that is presented in the later chapters. We describe the problem that inspired this research, provide a short overview of the empirical work reported in later chapters, and discuss and contextualize the findings and implications. Chapters 2, 3, 4, and 5, report the empirical work that forms the basis of Chapter 1. Chapter 2 addresses the first part of the aim of this dissertation, where we ask how people stick to misperceptions in the face of corrective information. Chapters 3, 4, and 5 address the second part of the aim, where we ask how science communication can improve to help people come to scientifically accurate beliefs. In Chapter 3, we meta-analytically test the effect of communicating consensus among scientists to the public. In Chapter 4, we aim to boost understanding and identification of scientific consensus to help correct false beliefs. Finally, in Chapter 5, we investigate the accuracy of coronavirus-related beliefs in the beginning of the COVID-19 pandemic and we try to apply our boosting strategy in this setting.

All chapters are published or submitted for publication in peer-reviewed journals and can be read independently.



CHAPTER 1

General Introduction and Discussion

An edited, Dutch version of this chapter is under review as:
van Stekelenburg, A. (under review). Ontkenning van de feiten: Hoe houdt men soms vast aan mispercepties over wetenschappelijke onderwerpen en hoe kan wetenschap beter gecommuniceerd worden? *Tijdschrift voor Communicatiewetenschap*

Correcting Misperceptions About Contested Topics Through Science Communication

The public does not agree about the facts surrounding a number of formidable challenges that the world is facing. One of the most pressing issues is that our planet is warming rapidly, with a rising sea level and more extreme weather events such as floods and extreme heat causing a public health crisis (IPCC, 2018). Urgent and fundamental changes are required, but substantial parts of the public still do not agree that we are causing the problem (e.g., Leiserowitz et al., 2020). Extreme weather will have disastrous, direct consequences, but it will also make meeting another challenge even harder than it already is: feeding the global population. An estimated two billion people do not have regular access to safe, nutritious, and sufficient food (United Nations, n.d.). Genetic engineering could make crops more resistant to extreme weather events (e.g., Khan et al., 2019) and enhance the nutritional value of our food (Hefferon, 2015), but is unwanted or illegal in many countries (Scott et al., 2018). On top of climate change and undernourishment, infectious diseases pose a third substantial risk to the health of countless people across the globe. After decades of successful immunization campaigns, diseases such as measles were eradicated in many countries. However, childhood vaccination rates are in decline in a number of regions of the world and some diseases are on the verge of making a comeback (Cunningham, 2020).

What do all these problems – climate change, undernourishment, and infectious disease – have in common? Their continued existence is at least partly the result of misperceptions. Misperceptions are factual beliefs that are false or contradict the best available evidence in the public domain (Flynn et al., 2017). There are many such false beliefs, especially regarding important and often discussed topics such as climate change, food safety, and vaccination. Common misperceptions about climate change are that it is not real or that even if it is, it is not caused by human action (e.g., Leiserowitz et al., 2020), making it unnecessary or impossible to take action against it. In other cases, people hold beliefs about issues that are not backed up by evidence, in a way 'creating' problems that hamstring our ability to deal with important challenges. Misperceptions about genetically engineered food center around the idea that it is unsafe to consume, because it might cause cancer or allergies (Scott et al., 2018). Similarly, even though misperceptions about vaccination vary widely, they often center around the suspicion that they are unsafe and that they might have adverse side effects such as autism or a weakened immune system (Geoghegan et al., 2020).

There are many examples of the fact that these misperceptions can have serious consequences. The US public elected a climate change denying president into office in 2016. During his term in office, he withdrew the US, the second largest contributor of CO2 emissions of all countries in the world (International Energy Agency, n.d.), from the Paris Climate Agreement, thereby substantially impeding the global effort against climate change. Meanwhile, opposition to genetically engineered food has resulted in many countries banning such ingredients in food (e.g., in Europe; European Parliament, 2015). According to estimations, in 2014 already, the ban on a type of fortified rice had cost India about 1.4 million life years in a decade (Wesseler & Zilberman, 2014). Regarding vaccination-related misperceptions, polls show that Europe is currently one of the leading world regions in vaccination skepticism (Wellcome, 2018). This is reflected in a record high in measles cases in the European Region in 2017 and 2018, after decades of decrease due to successful vaccination campaigns (European Centre for Disease Prevention and Control, 2020).

Solving problems begins with agreeing about the facts. Facts – information that is backed up by overwhelming scientific evidence – empower us to engage in informed dialogue, which is essential to meeting societal challenges and to democratic progress. While we acknowledge that one can never be 100% certain about anything, for pragmatic reasons, here, we use the term ‘facts’ to refer to information about which the scientific evidence is so overwhelmingly clear that society has to act on it. Although not everyone from the general public agrees, some of the most important facts related to the challenges that we face are clear, at least partly illuminating the road we have to take. Essentially, thus, important parts of these challenges are no longer facts problems, but facts communication problems.

To help the public understand and accept the facts surrounding important topics, science communication strategies play an important role. Science communication can be broadly defined as the use of appropriate skills, media, activities, and dialogue to produce science related awareness, enjoyment, interest, opinion-forming, and understanding (Burns et al., 2003). Science communication is broad and can be more than a one-way transmission of information (see Kappel & Holmen, 2019), but here we focus on efforts aimed at informing the public about facts and helping people understand science. In our supposed ‘post-truth’ world, a substantial number of science communication professionals and scholars worry that simply communicating the science does not work to inform the public of the facts. How is that possible? And can facts be communicated differently so they can inform the public? These questions are at the heart of the current work; the aim of this dissertation is to investigate how people stick to false beliefs in the face of corrective information and how science communication can improve to help people come to scientifically accurate beliefs.

The first part of this aim, asking the question how people stick to misperceptions in the face of corrective information, is addressed in **Chapter 2**. We look at one of the most prominent theories in evidence evaluation: the theory of motivated reasoning. More specifically, in this chapter we test how different motivations affect responsiveness to corrective science communication about vaccine and food safety. The second question, how science communication can improve to help people come to scientifically accurate beliefs, is addressed in the subsequent three chapters. In **Chapter 3**, we meta-analytically test the effect of one of the simplest and most studied science communication interventions aimed at informing the public: communicating consensus among scientists to the public. We combine effects of experiments about climate change, genetically modified food, and vaccination to investigate if scientific consensus messaging is effective in changing people's perceptions of scientific consensus and their belief in facts. Then, in **Chapter 4**, we aim to boost understanding and identification of scientific consensus to help correct false beliefs about climate change and genetically engineered food. In three experiments we first teach participants the value of scientific consensus and how to identify it and then present them with a news article reporting a scientific consensus opposing their false belief. Finally, in **Chapter 5**, we investigate the accuracy of coronavirus-related beliefs in the beginning of the COVID-19 pandemic. In this longitudinal study, we try to apply our boosting strategy in a more ecologically valid setting to improve belief accuracy.

How Do People Stick to Misperceptions?

For a long time in science communication, the audience was seen as a simple information processing machine. If the public is not aware of the facts, it was thought, this is due to a lack of knowledge, a 'deficit'. If the communicator sends information, the audience will absorb this information, filling the deficit, and adjust their beliefs and attitudes accordingly. This general idea is captured in the information deficit model of science communication (Gross, 1994; Sturgis & Allum, 2004). Decades of research into human cognition and communication have shown otherwise. Researchers have identified heuristics and biases, motivational processes, and other factors that affect human information processing (e.g., Kahneman et al., 1982; Kunda, 1990), meaning that changing beliefs might be more complex than just communicating facts.

One prominent theory related to reasoning about (scientific) evidence states that reasoning is affected by motivation, the goal one has when processing information. This theory of motivated reasoning (Kunda, 1990) forms the core of the first part of this dissertation, in which the objective is to investigate how people stick to false beliefs in the face of corrective information. According to the theory of motivated reasoning there are two broad categories of reasoning: reasoning where the goal is to arrive at the most accurate conclusion, whatever the outcome, and reasoning where the goal is to arrive at a preferred (directional) conclusion (Kunda, 1990). These motivational effects can already come into play even before someone is exposed to information, when they decide which information to consume. More specifically, people may avoid information that could be a threat to their preferred or pre-existing beliefs, leading to selective exposure (W. Hart et al., 2009).

Here we consider a situation, however, in which one is exposed to corrective information. Thus, we focus on the next step in motivated reasoning: motivated processing of information. Once an individual reads a message that counters something that they prefer to believe or already believe, they may engage in directional motivated reasoning to protect this belief (Kunda, 1990; also see Chen et al., 1999). The theory of motivated reasoning can explain the heartfelt supporter of the free market who believes that climate change is a hoax, because the preferred outcome of minimum climate change regulation directs reasoning toward believing climate change is not real. Similarly, pre-existing beliefs or behavior may be protected by directional motivated reasoning. A lifelong smoker might reject the evidence for a link between smoking and lung cancer, because accepting such a link means accepting that their health might be in serious danger and that they should stop smoking.

Thus, even though the source of the motivation may vary, people are sometimes motivated to come to a specific conclusion. The contrasting motivation, which is the goal to come to the most accurate conclusion, might make one more open to new information that is not in line with pre-existing or preferred beliefs (Kunda, 1990). Although considerable research has been conducted to identify sources of directional motivated reasoning (e.g., political partisanship, identity protection; Bolsen et al., 2014; Kahan et al., 2017), there was no research that tested if motivation affects responsiveness to corrective science information. Moreover, it was unclear whether misperceptions could be corrected more effectively by inducing an accuracy motivation in processing of such information.

Therefore, in Chapter 2, we investigated the causal role of motivated reasoning in the effectiveness of correcting misperceptions. We conducted two experiments. One focused on the misperception that giving young children multiple vaccinations overloads their immune system, the other focused on the misperception that food additives indicated with an E number are unsafe to consume. Importantly, to make certain that we were testing corrective effects of scientific information and to increase the chance that participants might be inclined to defend their belief, we specifically recruited participants who held the abovementioned misperception about vaccination (Experiment 1) or the misperception about E numbers (Experiment 2).

These participants were asked twice about their belief in a false statement related to vaccines or E numbers: once before we induced a motivation and presented corrective information and once after. This allowed us to investigate changes in participants' beliefs. We stimulated either directional motivation, accuracy motivation, or no specific type of motivation through a short instructional text (note that this last 'default motivation' condition was only included in Experiment 2). The corrective information looked like a short news article and refuted the false belief, explaining why it was false.

The results demonstrated that indeed motivation played a causal role in the effectiveness of a corrective science communication message: Accuracy-driven reasoning led to a larger corrective effect of the scientific information than reasoning driven by directional motivation. Interestingly, in the experiment about food additives, individuals' default reasoning (when we did not try to influence their motivation) made them just as receptive to the correction as accuracy-driven reasoning. This indicates that people might not be strongly inclined to engage in directional motivated reasoning just because they are confronted with information that opposes a belief that they hold. These findings support a more optimistic view of human receptivity to science communication than what was often found in the literature, which emphasized the possibility of corrective information 'backfiring' to strengthen misperceptions (P. S. Hart & Nisbet, 2012; Nyhan & Reifler, 2010, but see Nyhan, 2021; Swire-Thompson et al., 2020; Wood & Porter, 2019).

How Can Science Communication Improve?

Although it seems that people might be more receptive to corrective information than one might have expected, there are still substantial groups of people who hold misperceptions even after years or decades of exposure to accurate information (e.g., Pew Research Center, 2015). How can they be best informed about the facts? This question is related to the second goal of this dissertation: to investigate how science communication can improve to help people come to scientifically accurate beliefs. We will first discuss a prominent approach in science communication research to communicating scientific evidence – providing information about agreement among scientists – and then discuss a novel approach that we developed to help people make use of such information.

Communicating Scientific Consensus

We cannot and should not all be expected to understand the complexities of the earth's changing climate, gene editing, the human immune system, or many other important topics. One very promising strategy to inform the public is to communicate not the complexities of the scientific evidence, but the relatively clear information related to consensus among scientists (i.e., a high degree of agreement among scientists). This is an often studied intervention, especially in the domain of climate change (van der Linden, 2021). Scientific consensus messages are quite straightforward: They simply explain that there is a group of scientists who agree about a certain claim. An example of an often studied message is "97% of climate scientists have concluded that human-caused climate change is happening" (e.g., van der Linden et al., 2015).

The idea behind this strategy is that communicating scientific consensus will lead to an updated estimate of the scientific consensus, which in turn acts as a gateway to personal beliefs (Lewandowsky, Gignac, & Vaughan, 2013; van der Linden, Leiserowitz, et al., 2015). In addition to providing inherently valuable information, it relies on two heuristics: trust in experts and the idea that consensus implies correctness (van der Linden, 2021). However, there is debate about the effectiveness of scientific consensus communication in changing the public's beliefs (Landrum & Slater, 2020). Some researchers argue that the scientific consensus itself might not be accepted and might cause reactance among certain groups (Ma et al., 2019; see also Dixon et al., 2019; van der Linden, Maibach, et al., 2019). And even if the scientific consensus is accepted, it might not lead to people changing their personal beliefs about the facts (Bolsen & Druckman, 2018; Dixon, 2016; Pasek, 2018).

We decided to contribute to this debate by meta-analytically testing the effects of scientific consensus communication related to informing the public about three contested science topics. Specifically, in Chapter 3, we assessed the effects of scientific consensus communication regarding climate change, genetically modified food, and vaccination on 1) the perception that there is indeed a scientific consensus and 2) belief in scientific facts. Combining 43 experiments (total *N* = ~34,800), we found that across topics single exposure to consensus messaging had a positive effect on perceived scientific consensus. Additionally, it had a small but positive effect on factual beliefs. Importantly, it had almost no chance of backfiring; yielding negative effects on the accuracy of participants' beliefs. The results were very similar for climate change and genetically modified food, while not enough experiments were available to investigate the effects for vaccination separately. Thus, although the meta-analytic effect on beliefs was small, communicating scientific consensus appears to be a reliable way to change beliefs about contested science topics.

One important question remains: Does scientific consensus communication only help to further inform people who are already more or less on board or who might be unsure, or is it also useful to help people who hold misperceptions to accept the facts? As we have seen in Chapter 2, people who hold false beliefs might sometimes be motivated to protect these beliefs, making new information potentially less effective in informing them of the facts. We investigated this in the meta-analysis by exploring whether the effect of scientific consensus communication depended on participants' pre-existing belief. The results were inconclusive, possibly because there were not enough studies that had specifically recruited skeptics to test the effect of scientific consensus communication among this group. We addressed this potential limitation to the consensus communication strategy with a new approach in Chapter 4.

A second potential limitation to scientific consensus communication is reflected in criticism that consensus communication invokes scientists' authority as a means of persuasion (Pearce et al., 2015), as it may not be clear to everyone why scientific consensus is a valuable piece of information. Instead of only telling people what most experts believe, there might be an ethical advantage to helping the public figure out the facts themselves. This is particularly valuable in a time where science and scientists are regularly the object of mistrust or attack. We also addressed this limitation in Chapter 4.

Boosting Consensus Reasoning

A relatively new approach to decision-making and behavior change provides the ethical advantage of helping people figure out what is true, instead of only informing them of most scientists' beliefs. This approach is called 'boosting'. Boosting consists of noncoercive intervention strategies that aim to increase people's competence to make choices in line with their goals in a transparent way that promotes agency (Hertwig & Grüne-Yanoff, 2017; Lorenz-Spreen et al., 2020). A boosting approach to science communication might help people figure out the facts without potentially impeding their agency by relying only on a call to authority.

In Chapter 4 we employed such a boosting approach. Just as in Chapter 2, we specifically recruited participants who held a false belief to make certain that we were testing corrective effects. Specifically, we recruited participants who believed that climate change is not primarily caused by human action and participants who believed that genetically engineered food products are worse for health than food products that are not genetically engineered. In three experiments, these people holding a misperception first learned the value of scientific consensus and how to identify it. More specifically, we used an infographic to describe the process by which a scientific consensus develops and to provide three steps to identify information about a scientific consensus (look for a statement indicating consensus, check the source making the consensus statement, and evaluate the expertise of the people who came to a consensus). Subsequently, participants read a news article containing information about a scientific consensus opposing their false belief.

We found that the two-step communication strategy, boosting combined with information about scientific consensus, was more successful in correcting a misperception related to genetically engineered food than only communicating scientific consensus. The results related to climate change were inconclusive, however, indicating that this approach may not work for misperceptions about this topic. These findings suggest that a strategy of open communication about the value and process of reaching a scientific consensus can sometimes help to correct misperceptions.

Together, the meta-analytic and experimental work suggest that scientific consensus communication, especially when combined with boosting understanding and identification of scientific consensus, can be effective not only in strengthening accurate beliefs but also in correcting false beliefs.

An important limitation of the work reported in Chapter 3 and Chapter 4 is that only short-term effects of single exposure to the intervention were examined in controlled experimental settings. Initial findings in one of the experiments in Chapter 4 from a two-week follow-up were inconclusive. These limitations are also evident in many other studies in this domain (van der Linden, 2021; also see Kahan & Carpenter, 2017). Consequently, it is yet unclear if and how corrective effects, such as those found in the meta-analysis and in our experiments, translate to real-life settings. Both for science communication practice and for theorizing about corrective science communication and boosting it would be very valuable to know if these effects persist in less controlled environments, and if bigger, durable effects can be achieved through repeated exposure.

Hence, in Chapter 5, we attempted to apply our boosting approach in a more naturalistic setting during the COVID-19-pandemic. In contrast to misperceptions about climate change and genetically engineered food, beliefs related to the novel coronavirus and COVID-19 were still very recent and fluctuating. This makes correcting beliefs by communicating scientific consensus problematic, because you have to constantly target new mispections. Thus, we changed and tested our boosting intervention to not only help people understand and identify scientific consensus, but also to search for it. Additionally, we attempted to gain insight into public beliefs about the novel coronavirus and COVID-19 in one of the worst hit countries at that time: the United States.

Four times over a period of four weeks we asked a balanced sample of participants (balanced regarding age, gender, and ethnicity to approximate the US general public) to indicate to what extent they believed a number of true and false statements. In contrast to the experiments from Chapter 4, we did not pair the boosting intervention with a news article containing corrective information. Thus, people had to put their new skill to use outside the study context. The results demonstrated that most people were quite able to figure out the facts in these relatively early days of the crisis; a large majority of the participants did not hold any misperceptions. Moreover, beliefs that were measured at multiple times slowly became more accurate over the weeks. This was not due to our boosting intervention, however. Even for those individuals that held relatively less accurate beliefs than average at the start of the study, the intervention was not successful in increasing their belief accuracy compared to control. This highlights the difficulty of translating lab-based effects into real-world settings.

Conclusions and Implications

What do these studies tell us about how people stick to false beliefs in the face of corrective information and how science communication can improve to help people come to accurate beliefs? First, they demonstrate that people can sometimes stick to misperceptions when faced with corrective information because they are motivated to do so. Our research demonstrates that reasoning about corrective information with the goal to reach a predetermined conclusion can lead to less belief updating than reasoning with the goal to come to the most accurate conclusion (Chapter 2). This is an important first step in uncovering the causal effect of motivation in reasoning, but we note that there are some alternative explanations that need to be taken into account (e.g., the possibility that demand effects might have caused some of the differences between conditions; see Strengths, Limitations and Suggestions for Future Research).

Second, the findings show both meta-analytically (Chapter 3) and experimentally (Chapter 4, Experiment 3) that science communication can improve by leveraging the informational and heuristic value of scientific consensus. Although the effect of single exposure to scientific consensus messages on factual beliefs might be small – the meta-analytically estimated effect was smaller than the median effect size in communication science (Rains et al., 2018) – communicating scientific consensus appears to be a reliable way to change beliefs about contested science topics. This small effect might be magnified over time to be practically meaningful (e.g., with repeated exposure; Anvari et al., n.d.; Funder & Ozer, 2019) and could be larger when scientific consensus reasoning is boosted.

Helping people identify and understand scientific consensus can help reduce misperceptions, at least in the case of genetically engineered food (Chapter 4, Experiment 2 and Experiment 3). It is uncertain, however, whether such interventions focused on boosting consensus reasoning are also effective for topics where trust in scientists is generally somewhat lower (e.g., climate change; Chapter 4, Experiment 1). Additionally, our results show that effects of single exposure to such interventions might be unstable over a longer time period (i.e., two weeks; Chapter 4, Experiment 2) and that applying such interventions outside controlled experimental settings can be difficult (Chapter 5).

Along the way, we have found some reasons for optimism about people's beliefs and acceptance of scientific information. Chapter 2, Experiment 2, shows that individuals' default reasoning about corrective information made them just as receptive to the corrective science communication message as accuracy-driven reasoning. This suggests that people might be less likely to protect existing or preferred beliefs in the face of corrective information than one would expect from the previous literature. Moreover, the overall corrective effects from the experiments in Chapter 2 and Chapter 4 were quite large for single exposure to corrective information. Although we note caution when interpreting overall differences between pretest and posttest scores due to regression to the mean (a statistical phenomenon that can make natural variation in repeated data look like real change; Barnett, 2004), these differences might suggest that people generally are quite willing to update their beliefs when confronted with corrective information. Finally, Chapter 5 shows that even in the relatively early days of the COVID-19 pandemic, where there was much worry about misinformation, most people were quite able to figure out the facts. And even if initially there was some uncertainty, a general increase in belief accuracy over the four-week period we surveyed suggests that people are able to figure out the facts over time.

Science Communication Theory

These findings stand in striking contrast to some of the prevailing ideas in the field, which until recently was rife with the suggestion that corrective information is likely to backfire and strengthen misperceptions. Our research is not the only recent research that suggests this idea may be false. Other recent work has compellingly demonstrated that the backfire effect is very unlikely to occur (Nyhan, 2021; Swire-Thompson et al., 2020; Wood & Porter, 2019). Nonetheless, this backfire effect, among other findings, has contributed to the end of the information deficit model of science communication and its assumption that disagreement with scientific evidence is a result of insufficient knowledge (Drummond & Fischhoff, 2017; P. S. Hart & Nisbet, 2012; Hornsey et al., 2018; National Academy of Sciences, 2017; Simis et al., 2016).

Our findings are partly in line with the reasoning against the deficit model, but provide nuance. Indeed, we also find, as suggested by the theory of motivated reasoning, that people's goals can influence how effective corrective science communication can be in correcting misperceptions. However, we find no evidence of a backfire effect. In contrast, our research suggests that people who hold misperceptions, even when they may be motivated to protect a pre-existing or preferred belief, will come to relatively more accurate beliefs after exposure to corrective information. Additionally, we show that quite straightforward scientific consensus messages, which merely provide information, are effective in changing beliefs and are again very unlikely to backfire.

We believe that our research, combined with other recent empirical work (e.g., Anglin, 2019; Nyhan et al., 2020; Ranney & Clark, 2016), demonstrates that the main reasoning behind the information deficit model may have been disregarded too soon. Even though people are clearly no 'information processing machines' and our reasoning can be biased in numerous ways, providing information can often work to correct false beliefs and reduce skepticism to facts. This might seem at odds with the theory of motivated reasoning, but it does not have to be. Instead, we argue that people might be most inclined to employ accuracy-motivated reasoning, while primarily directional reasoning is rare and could very well be limited to very specific subgroups or circumstances.

The partial success of our boosting approach, which empowers people to find out the facts using scientific consensus, can also be argued to be in line with the reasoning captured in the information deficit model. The main premise of the model is that a lack of knowledge or understanding leads to skepticism and that filling this deficit will lead to acceptance of the facts. Our boosting approach, which focuses on understanding, seems to be able to make simple information even more effective in communicating facts. This highlights the potential of two roads to accurate beliefs that should be distinguished in the deficit model: providing corrective information and empowering understanding of science in general. For theorizing in science communication research, the field might do well to focus on these two roads. Particularly, boosting approaches that empower people to come to the most accurate conclusion warrant more scholarly attention.

Science Communication Practice

In scientists' communication practice, there is still substantial pessimism about the general public's willingness to accept facts (Simis et al., 2016). This pessimism is also found among journalists and other communicators, and is reflected in popular media. In 2016, following the UK Brexit referendum and the US presidential elections, Oxford Dictionaries declared 'post-truth' the international word of the year (BBC News, 2016). Numerous magazine articles appeared claiming that facts were not enough to convince people anymore (e.g., Beck, 2017; Kolbert, 2017). But even before 2016, there was worry in popular media about facts backfiring, for instance in the context of vaccine hesitancy (e.g., Romm, 2014). In 2020, the COVID-19 pandemic put the spotlight on much of this worry, now compounded by fear of widespread misinformation. The World Health Organization declared that the world was not only suffering from a pandemic, but also an 'infodemic': an excessive amount of accurate and inaccurate information (World Health Organization, 2020).

The implications of our work for science communication practice are simple. Science communicators would do well to start out from a more optimistic viewpoint of human receptivity to scientific information. Many people seem to be receptive to scientific evidence. One promising method of communicating the weight of scientific evidence is communicating scientific consensus. Such messages appear to be quite rare in news in general (Merkley, 2020) and specifically in news about climate change (Chinn, 2021). Conversely, common journalistic practice to provide balance in news, for instance by including both the perspective of a medical professional and that of an anti-vax parent, may result in portraying a false balance. This puts people at risk of wrongly perceiving some kind of uncertainty in the evidence. Therefore, when there is overwhelming scientific evidence for a specific position, science journalists should consider conveying the weight of this evidence instead of balancing viewpoints. Similarly, others, such as scientists, medical professionals, or governmental and non-governmental organizations aiming to inform publics of the scientific facts, should be aware of the potential of communicating agreement among scientists. A climate scientist hoping to inform a policymaker about the reality of man-made climate change might consider highlighting the fact that almost all of their climate scientist colleagues agree on this point. This consensus communication strategy comes at a low cost and consists simply of informing people.

We do not argue that only providing corrective information will always work, but we do argue that it might work more often than one would expect based on a reading of the academic literature or popular media articles. In some situations, however, certain groups might not be very responsive to simple information messaging. Selective exposure might make it difficult to gain people's interest for news or other types of information that might contradict pre-existing or preferred beliefs (W. Hart et al., 2009; though also see Barberá et al., 2015; Garrett, 2009). Additionally, people might be misinformed by other sources of information, such as friends and family, politically slanted news, or misinformation. In those situations, it might help to empower information consumers to be better able to understand and identify important information. Although more research is needed, this dissertation shows that empowering the public to be better able to understand the scientific process and the value of scientific evidence is a promising place to start. Herein lies a responsibility for all science communicators, from scientists to journalists to governments, to help the public understand and appropriately value the information that is conveyed. Note that while ethically the preference might be on empowerment over persuasion, in certain situations empowerment might be complimented with more specific 'persuasion-like' interventions, such as value-based messaging (e.g., Dixon et al., 2017) or framing (e.g., Bolsen et al., 2019).

Strengths, Limitations and Suggestions for Future Research

We will highlight three strengths of the current work, before we take note of a number of limitations. The first strength pertains to the samples that were recruited for the experiments in Chapter 2 and Chapter 4. The main focus of the research reported in these chapters was on misperceptions, investigating how people might stick to false beliefs and how they can be corrected. We recruited participants who held misperceptions, which allowed us to investigate our research questions in the most relevant population. For various reasons, most previous work had recruited samples of the general population, often consisting of participants who already more or less accepted the facts. However, it is difficult to draw conclusions about motivated reasoning and protection of pre-existing beliefs if participants were not selected based on their motivation or pre-existing beliefs. Similarly, conclusions about 'corrective effects' should be drawn from experiments with a sample of participants who hold a false belief to correct.

Second, in this dissertation we make an attempt to acquire insights that are generalizable across topics. We understand that the challenges that we face, climate change, undernourishment, and infectious diseases among others, are important enough to warrant their own communication research. However, the fragmentation of science communication research puts a big question mark on the generalizability of much of its results. Can the accumulated knowledge regarding climate change communication, for instance, be put to use in communication about genetically engineered food or vaccination, or other topics even? We have attempted to contribute to some of the first steps to answer these questions. Our approach, meta-analytically comparing communication about different topics and replicating results of experiments with different topics, is one of the strengths of the current work. It allows for broader and more generalizable insights into communication about contested science topics. If we want to be able to meet future challenges, we need to acquire more such knowledge that transcends single topics.

A third strength is found in our use of open science practices. All four empirical chapters are freely available online, allowing anyone to read our work. All studies were preregistered, making our research process transparent. All data and material of published works are freely available online (see my Open Science Framework profile: www.osf.io/uwzky), making our research reproducible and replicable. This transparency is not only valuable for other scientists interested in our work, but is especially important in a time where science is regularly under attack. The rise of populism has not only led to an anti-elite rhetoric, but also fueled an anti-science rhetoric (Mede & Schäfer, 2020). Open science might strengthen the public's trust in science (Grand et al., 2012). We believe that if scientists want the public to value scientific evidence, scientists should be as open and transparent as possible in the research process.

A limitation of our work is that most of our studies, as well as most of the studies included in the meta-analysis in Chapter 3, were conducted in controlled environments. Such environments do not reflect daily life and might be subject to demand effects, where participants may display different behavior because they form an interpretation of the purpose of the experiment (Orne, 1962; though see Mummolo & Peterson, 2019). Moreover, we mostly tested direct effects of single exposure to corrections. In contrast, a real-life situation might be better reflected in longitudinal studies with multiple exposures to corrective communication. As illustrated by the slow acceptance of the link between smoking and lung cancer, but also the slow but ongoing acceptance of human-caused climate change, influential misperceptions can take decades to correct at the population-level. Future research would do well to test effects of corrective science communication in a better reflection of the complex media landscape, as well as to investigate long-term effects of (repeated) exposure (for a notable example, see Goldberg et al., 2021).

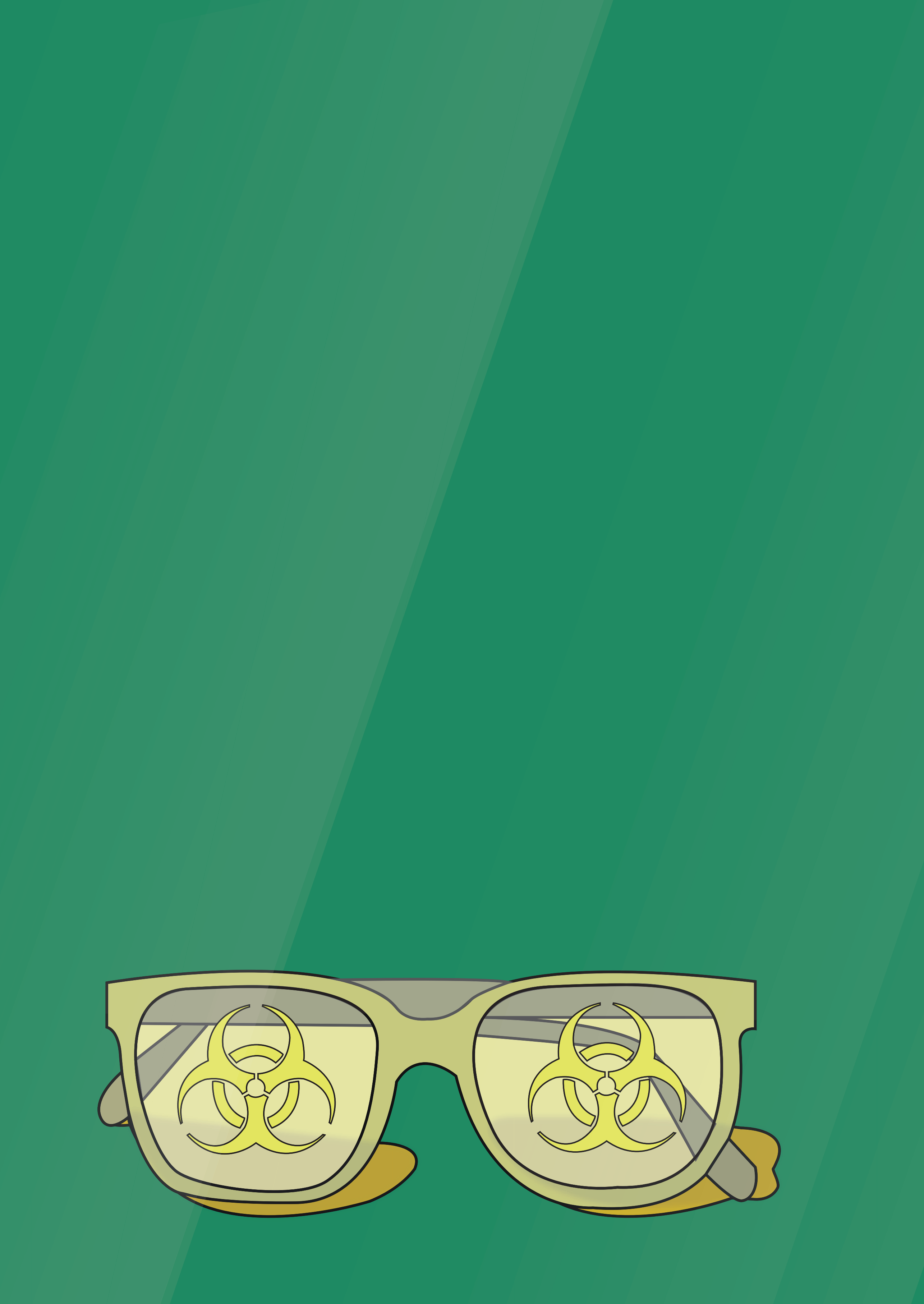
Another limitation is related to how we recruited participants for most research in this dissertation. With the exception of the meta-analysis and one pilot study, all observations are derived from participants recruited through online crowdsourcing platform Prolific (www.prolific.co; Palan & Schitter, 2018). Importantly, the platform allowed us to screen potential participants such that we were able to recruit people holding misperceptions (for Chapter 2 and Chapter 4), recruit a balanced sample of the US population (for Chapter 5), and it provides good data quality (Peer et al., 2017). However, it is possible that the sample on Prolific is different from the general population in systematic ways, for instance because it is known to mostly host academic research. This puts a question mark on the generalizability of our results and re-emphasizes the need for more fieldwork.

We would like to highlight one point that can be seen both as a strength and as a limitation of the current work: our focus on beliefs instead of behavior. One might wonder whether beliefs even matter when we try to tackle immense challenges like climate change, undernourishment, and infectious diseases. Would it not be more effective to focus on changing behavior, for instance by aiming to reduce behavior producing high carbon emissions, instead of changing beliefs? We argue that rather than focusing only on behavior, both changing beliefs and changing behavior are valuable in meeting these challenges. Changing behavior is a whole different ballgame than changing beliefs, other interventions and policy are useful in this regard. Notably though, climate change campaigners trying to limit carbon footprints, policymakers hoping to harness the potential of genetic engineering technology, and health professionals aiming to increase vaccine uptake face an uphill battle if the people they work with do not ascribe to the same reality as they do, if they do not acknowledge the same facts as they do. Moreover, democracy can only thrive if the public is aware of the facts surrounding the challenges a country is facing, instead of, as we have seen in recent major democratic events around the world (e.g., the Brexit referendum, the 2016 US presidential elections, the 2018 Brazilian presidential elections), being lied to. Third, with substantial time and money flowing from society into academic research, we believe that academics have a moral obligation to try to inform the public of the results of their work.

Finally, we have a more general suggestion for future research. Scholarly attention that was reserved for investigation of the backfire effect might instead be better used to provide a proper test of the information deficit model. To be able to do that, however, the deficit model and its broad predictions first need to be specified more clearly. The lack of a clear definition of the deficit model has led to it being an easy focus of criticism, being used as a “straw man” (Sturgis & Allum, 2004). We believe that the core predictions, that 1) public skepticism towards science is caused by a lack of understanding or knowledge and 2) that communicating scientific information to fill this deficit would lead to acceptance of facts, can be valuable if specified with testable hypotheses. What type of scientific information should be communicated and what exactly is expected to change: beliefs and attitudes, or more? What are the boundary conditions of these predictions? These are all important questions for science communication research and practice.

Concluding Remark

We are facing a number of formidable challenges and these challenges are partly perpetuated by misperceptions. There is reason to be optimistic, however. Many people are receptive to scientific information; they will adjust their beliefs when confronted with corrective information. Of course, ‘truth’ cannot and should not be communicated top-down from science to society, but scientific evidence should be communicated clearly as part of the dialogue between science and society. Substantial amounts of society’s time, effort, and money are invested in science. We should not let it go to waste. Agreement about the evidence and about the facts empowers us to meet societal challenges. This process may take a long time. Some topics were contested for decades among the public while the scientific evidence was clear, such as the link between smoking and lung cancer. There are topics about which we are finally reaching overall acceptance of the facts, like climate change. But there are also topics for which the biggest challenges may yet come, for instance when genetically engineered food becomes more widespread. And even when almost everyone agrees about the facts, science communicators should stay vigilant, as is demonstrated by the rise of vaccine-related misperceptions in some areas of the world. With the acquired knowledge, we hope to be able to contribute to an improving science communication practice and to provide insights for future science communication research. Hopefully, we can be prepared not only to face current challenges, but also to live up to future ones.



CHAPTER 2

Correcting Misperceptions: The Causal Role of Motivation in Corrective Science Communication About Vaccine and Food Safety

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Abstract

Some people stick to beliefs that do not align with scientific consensus when faced with science communication that contradicts those misperceptions. Two preregistered experiments (total N = 1,256) investigated the causal role of motivated reasoning in the effectiveness of correcting misperceptions. In both experiments, accuracy-driven reasoning led to a larger corrective effect of a science communication message than reasoning driven by directional motivation. Individuals' default reasoning made them just as receptive to the correction as accuracy-driven reasoning. This finding supports a more optimistic view of human receptivity to science communication than often found in the literature.

Keywords: misperceptions, motivated reasoning, science communication, vaccination, food safety

Correcting Misperceptions: The Causal Role of Motivation in Corrective Science Communication about Vaccine and Food Safety

Some people hold beliefs that do not align with the scientific consensus. And some of them stick to these misperceptions, even when they are faced with evidence that directly contradicts their beliefs (e.g., Holman & Lay, 2018; Nyhan & Reifler, 2010; Nyhan, Reifler, & Ubel, 2013). The current research investigated the causal role of motivation in holding on to misperceptions about scientific facts in the face of corrective science communication. To what extent is sticking to misperceptions driven by directional motivated reasoning? And can reasoning be influenced to increase the effectiveness of corrective information?

Vaccine and Food Safety

Misperceptions are factual beliefs that are false or contradict the best available evidence in the public domain (Flynn et al., 2017). They can be very harmful, for example when they are related to health issues. Two health issues that suffer from misperceptions are vaccination and food safety. While vaccination programs are one of the most successful health interventions in the history of humankind, a notable proportion of the general public is skeptical of vaccines (Larson et al., 2016). This skepticism influences the decision to vaccinate (Joslyn & Sylvester, 2019), which can have very harmful consequences. For instance, preliminary data from 2019 indicate that measles cases have spread fast among clusters of unvaccinated people in countries with high overall vaccination coverage (World Health Organization, 2019). Furthermore, in the US, vaccine refusal has been linked with outbreaks of vaccine-preventable diseases (Phadke et al., 2016). Trends such as these have led the World Health Organization to classify vaccine hesitancy as one of the most important threats to global health in 2019, together with threats such as climate change and HIV (World Health Organization, n.d.).

Focusing on the second issue, food safety, a primary example of harmful misperceptions can be found in beliefs about E numbers. E numbers are used in Europe to identify food additives and were introduced to reassure consumers that additives indicated with these numbers are safe to consume. Food additives indicated with E numbers can have important functions, such as preventing the growth of harmful bacteria that cause potentially fatal diseases like botulism (Food Standards Agency, 2018). Paradoxically though, E numbers have evolved into a cause of worry among consumers over the safety of these additives (Haen, 2014; Saltmarsh, 2015). The misperception that these additives are unsafe can have serious negative consequences for food production, with food producers forced to look for costly replacements for safe and tested food additives. Moreover, consumers' food choices likely suffer from avoiding food products that are actually safe to eat (Shim et al., 2011).

In the current research, we focused on correcting one misperception related to vaccination and one misperception related to food safety. By studying two different topics, we tested whether our findings are generalizable to diverse topics of misperceptions. In the first experiment, we provided corrective information to the misperception that childhood vaccines can 'overload' a child's immune system. In the second experiment, we provided corrective information to the misperception that food additives indicated with E numbers are unsafe to consume. Correcting such misperceptions is important because these beliefs inform opinions on important policy, such as policy about unvaccinated children going to day-care, and behavioral intentions, such as the intention to avoid safe to consume food products. These beliefs may even be determinants of behavior (e.g. Joslyn & Sylvester, 2017). In addition, having an informed citizenry is a valid goal in itself.

Motivated Reasoning

Misperceptions can be difficult to correct because people are biased information processors. One important psychological source for bias is called directional motivated reasoning (Kunda, 1990). This means that one has a directional goal in reasoning, for instance a preferred outcome. A directional goal can lead to biased reasoning in support of that goal. This type of reasoning explains the heartfelt supporter of the free market who believes that climate change is a hoax, because the preferred outcome of minimum climate change regulation biases reasoning towards believing climate change is not real. Similarly, directional motivated reasoning can explain the heavy smoker who rejects the evidence for a link between smoking and lung cancer, because one prefers to be able to smoke without having to worry about negative health effects. It can even explain paradoxical findings of corrective messages leading to 'backfire' effects (P. S. Hart & Nisbet, 2012; Nyhan et al., 2013; Nyhan & Reifler, 2010; Zhou, 2016): directional motivation can make one counterargue the corrective message, thereby strengthening the original misperception.

While numerous studies have focused on identifying sources of directional motivated reasoning, evidence for a causal role of directional motivated reasoning in holding on to misperceptions in the face of corrective information is to date limited. Previous research identified prior beliefs as a general source of directional motivated reasoning (e.g., Lord, Ross, & Lepper, 1979; Taber & Lodge, 2006), as well as more specific sources such as partisanship (Bolsen, Druckman, et al., 2014; Gaines et al., 2007; McCright & Dunlap, 2011) and related sources such as identity protection (Kahan et al., 2017; Lyons, 2018), conspiracy ideation and worldviews (Lewandowsky, Gignac, & Oberauer, 2013), and solution aversion (Campbell & Kay, 2014). Research on the causal effect of directional motivated reasoning in sticking to misperceptions, however, is difficult because one cannot easily manipulate an individual's political ideology or worldview. To test a causal link between directional motivation and holding on to misperceptions, experiments where motivations are manipulated are needed to disentangle the effects of motivation from other processes (Leeper & Slothuus, 2014). This can be done, for instance, by seeking ways to experimentally induce directional motivated reasoning (Nyhan & Zeitzoff, 2018).

There is some experimental research on the causal effect of directional motivated reasoning on opinion formation (Bolsen, Druckman, et al., 2014; Bolsen & Druckman, 2015). This effect is demonstrated by comparing directional motivated reasoning to accuracy motivated reasoning. In contrast to directional motivated reasoning, an accuracy-motivated individual has the goal to come to what is believed to be the most accurate conclusion (Kunda, 1990). This experimental research has shown that inducing accuracy-driven reasoning has the potential to reduce the biasing effect of directional motivation on opinion formation (Druckman, 2012), for instance regarding support for energy policy (Bolsen, Druckman, et al., 2014) and emergent energy technologies (Bolsen & Druckman, 2015). However, it is unclear whether these effects on opinion formation generalize to factual beliefs. Opinions are more subjective than factual beliefs, possibly making them more receptive to effects of motivated reasoning than, for instance, factual beliefs about the safety of vaccines. Nonetheless, these findings suggest that inducing accuracy motivation might be a suitable intervention to increase the effectiveness of corrective science communication in the face of misperceptions. Yet, there is a lack of studies on inducing accuracy motivation. Understanding when accuracy-driven reasoning overtakes directional reasoning is important in studying misperceptions (Druckman & McGrath, 2019; Flynn et al., 2017).

The current research aims to fill these gaps. The aim was to study the causal role of directional motivated reasoning in holding on to misperceptions in the face of corrective science communication and to investigate whether inducing accuracy motivation can aid in correcting misperceptions. We explored, not hypothesized, potential effects of directional motivation on policy opinions and intentions, because results in the literature regarding these second order outcomes are mixed (Flynn et al., 2017; Nyhan & Reifler, 2015). We conducted two preregistered experiments in which a science communication message was used to correct a misperception. In both experiments, the message itself was effective in reducing endorsement of the misperception. More importantly, type of motivation in processing of the message affected how strong the corrective effect of the messages was, with accuracy-driven reasoning leading to a larger correction than directional motivated reasoning. Our findings also partially demonstrated that the influence of motivation was not limited to the misperception itself, but extends to second order outcomes policy support and intentions.

Experiment 1 – Vaccine Safety

In the first experiment, a vaccine-related misperception was corrected. By measuring endorsement of the misperception before (prior) and after (posterior) motivation was manipulated and corrective information was presented, we could expose all participants to the corrective message while investigating the influence of motivation. Based on previous research on motivated reasoning (Bolsen, Druckman, et al., 2014; Bolsen & Druckman, 2015), we believed that an accuracy-motivated individual would be more susceptible to corrective information than a directionally motivated individual. Therefore, we expected that inducing accuracy motivation would lead to lower posterior endorsement of the misperception than inducing directional motivation, while controlling for prior belief certainty.

Hypothesis 1: Inducing accuracy motivation will lead to lower posterior endorsement of the misperception than inducing directional motivation, while controlling for prior belief certainty.

Although accuracy motivation may amplify the corrective effect of a science communication message, the effect of motivation on a belief is subject to reality constraints (Kunda, 1990; Molden & Higgins, 2005). When one holds a belief about reality with high certainty, the degree to which motivation can affect the interpretation of new information regarding that belief is constrained. For instance, you might be motivated to believe that you are 20 cm taller than you actually are, but if you are already certain about your true height any such motivational effects on this belief should be limited. Therefore, we expected that when individuals were very certain of their prior belief the effect of motivation would be limited, while under uncertainty the effect of motivation should be larger. Specifically, we expected that motivation would interact with prior belief certainty, such that the more certain the prior belief was, the smaller the corrective effect of accuracy motivation on the posterior belief would be.

Hypothesis 2: Motivation will interact with prior belief certainty, such that the more certain the prior belief is, the smaller the corrective effect of accuracy motivation on the posterior belief will be.

Method

Amongst others, the hypotheses, sampling procedure, main analyses, and exclusion criteria were preregistered on the Open Science Framework (OSF; https://bit.ly/2P2EGdP). Initially, successful completion of an instructional manipulation check (IMC; see Measures) was included as one of the exclusion criteria. IMCs are used to detect whether participants read the instructions and can increase statistical power and reliability of the data (Oppenheimer et al., 2009). After collecting data from 38 participants, we decided that the IMC was too sensitive. Based on the IMC we needed to exclude 31 participants (81.58%), who actually appeared to complete the experiment seriously, as indicated by completion times (*M* = 474.23 s), reading time of the corrective information (*M* = 83.88 s) and coherence of responses to open questions. We believe that the overly sensitive IMC may be due to the instructions of the IMC being irrelevant to the question that was asked, not due to a lack of effort on the side of the participants. Therefore, this exclusion criterion was dropped. The preregistration was updated to reflect this new exclusion criterion (https://bit.ly/2Ry9SU4). We chose to keep the data for exploratory analyses (total N = 404), for ethical reasons (i.e. not wasting participants' serious responses). The manipulation check and main analysis (reported below) included only those participants who participated in the experiment after the preregistration was updated (n = 372).

All data and the R script for the analysis can be found on the project page on the OSF (https://bit.ly/2Pv1mlY). Both Experiment 1 and Experiment 2 (see below) are part of a research project that was reviewed and approved by the Ethics Committee Social Science at Radboud University (ref. ECSW-2018-056).

Participants and design. Participants were screened and recruited using online crowdsourcing platform Prolific. Prolific has been demonstrated to yield high quality data and more diverse participants than student samples or other major crowdsourcing platforms (Peer et al., 2017). We screened participants prior to the experiment on whether they endorsed the misperception. They were presented with a list of five statements, including the misperceptions from Experiment 1 and Experiment 2 (see below) and were asked to select all of the statements they believed to be true. Only participants who indicated the statement "Giving young children multiple vaccinations overloads their immune system" was true were eligible for participation in the experiment.

Following a Bayesian sequential sampling procedure with optional stopping and maximum N (Schönbrodt et al., 2017), 542 participants (UK nationals) were recruited. Participants each received £0.85 for participating in the experiment. During the sequential sampling procedure, we checked the Bayes Factor (BF) at predetermined intervals to evaluate the evidence in the data for or against the first hypothesis. The advantage of this procedure is that it allows for efficient data collection. No more or less data are collected than necessary for a specified level of certainty, since the BF indicates both evidence for an effect and evidence in favor of no effect. We continued data collection until there was strong evidence ($0.1 > BF_{01} > 10$; Schönbrodt et al., 2017) in favor or against our first hypothesis. We started checking the BF for the hypothesized effect when 171 participants (enough to detect a medium effect size with 0.90 power and alpha = .05; Faul, Erdfelder, Buchner, & Lang, 2009) completed the experiment and continued to check it after every set of 50 new participants. If at any time the BF reached the required level of evidence for or against the hypothesis, data collection would be stopped. This was never the case, therefore data collection continued until the maximum N of 500 participants (excluding participants from before the updated preregistration).

We collected data from a total of 542 participants. Three participants who completed the experiment too fast and one that did not participate through Prolific were excluded (not preregistered). This resulted in the planned 538 participants, of which 500 participated after the updated preregistration. At the start of the experiment, participants indicated their endorsement of the misperception. Even though we screened participants before the experiment on whether they held the misperception, only 407 (75.65%) indicated that they endorsed the misperception at the beginning of the experiment (score > 0 on the misperception measure; see Measures). As we are interested in correcting misperceptions, only these participants were included in the analyses. Three participants who did not understand the misperception measure were identified by means of an open answer question in the experiment. Their response to the open answer question indicated a large correction in their endorsement of the misperception, but their response on the misperception measure conflicted with this. They were excluded post-hoc. This resulted in 404 participants (269 female, 135 male, M_{Age} = 38.95, SD_{Age} = 12.73) in the total dataset, of which 372 participated after the updated preregistration.

The experiment consisted of a one-factor (motivation in reasoning; accuracy-driven reasoning vs. directional reasoning) between-subjects design. In one condition accuracy motivation in reasoning was induced (n = 209), in the other condition directional motivation in reasoning was induced (n = 195).

Materials and procedure. The experiment was conducted using Qualtrics survey software. First, prior endorsement of the misperception was measured. Subsequently, participants were randomly assigned to two conditions. They were instructed to read a text either in a way that induces directional motivation or in a way that induces accuracy motivation, based on Bolsen, Druckman, and Cook (2014). We piloted an earlier version of the manipulation in a preregistered experiment (https://bit.ly/2rwk2Ka). Based on the results of that pilot we made some improvements to the manipulation. The instructions in the directional condition (85 words) included telling participants that we were interested in their judgment because they believed that vaccines can overload a child's immune system and asking participants to be aware of this belief when reading the upcoming text. Furthermore, we asked them to apply their perspective, and to think of what would confirm their initial belief. The instructions in the accuracy condition (79 words) included telling participants we were interested in their judgment because we studied how people process information and come to conclusions and asking participants to be even-handed. Furthermore, we asked them to apply various perspectives and to think of what would disprove their initial belief (for the full texts, see Appendix A). Participants were required to stay on the page with the instructions for at least 10s. After 10s, the button to continue to the next page appeared, which included the text "I will be aware of my belief and view the information from my perspective. I will try to think of what could confirm my initial belief" (directional condition) or "I will view the information in an even-handed way and from various perspectives. I will try to think of what could disprove my initial belief" (accuracy condition).

Both groups were then presented with the science communication message (386 words), which contained information correcting the misperception. The information was based on information from Science Magazine (Hickok, 2018), the NHS (National Health Service, 2016), the University of Oxford Vaccine Knowledge Project (Vaccine Knowledge Project, 2018), and the American Academy of Pediatrics (American Academy of Pediatrics, 2008). The text explained that vaccines do not overload children's immune system and that this knowledge is based on many scientific studies. One recent study was explained in more detail and an explanation was given of why vaccines do not overload the immune system. A graph was included in the text (see Appendix B for the full message).

After reading the corrective text, participants' endorsement of the misperception was measured again (the posterior belief). We explained to participants that this second measure was not a test, but that we were interested in their belief. The remaining variables were measured, amongst which was an open answer question in which participants were asked to give a short justification for their answer on the measure of posterior endorsement of the misperception.

Measures. Endorsement of the misperception was measured twice, once at the beginning of the experiment and once after the motivation manipulation and corrective message. This not only increased power to detect an effect, but also allowed us to investigate both the corrective effect of the message itself and the effect of motivation on receptivity to this message. Endorsement of the misperception was measured by asking participants to what extent they believed the following statement to be true: "Giving young children multiple vaccinations overloads their immune system". Their response was measured on a visual analogue scale (VAS) ranging from *I am 100% certain this is false* (-100) to *I am 100% certain this is true* (100) with *I don't know* in the middle (0). Since we included only those participants that endorsed the misperception at the beginning of the experiment, the prior score on endorsement of the misperception is simply a score of how certain they were of their belief in the statement (i.e. prior belief certainty).

The manipulation check consisted of six statements. Half of these statements reflected the instructions from the directional motivation condition (e.g., "While reading the information I tried to view the information from my perspective"), the other half were in line with the accuracy motivation instructions (e.g., "While reading the information I tried to view the information from various perspectives"). Responses were measured on a 7-point scale ranging from *Strongly disagree* to *Strongly agree*. Average scores were calculated for following the directional and accuracy motivation instructions separately.

Several exploratory variables were measured at the end of the experiment. Perceived change in belief certainty was measured by asking participants if they became more or less certain of their initial belief, measured on a VAS ranging from *I am much less certain now* (-50) to *I am much more certain now* (50), with *My certainty has not changed* in the middle (0). Support for policy aimed at stimulating people to vaccinate their children and intention to vaccinate one's children were measured with responses to single statements. Open-minded cognition (OMC) was measured using the open-minded cognition scale developed and validated by Price, Ottati, Wilson, and Kim (2015). Trust in the National Health Service (NHS), trust in scientists, perceived reliability of the information provided to the participant, perceived knowledge of vaccines, and importance of the topic were measured with single response items. All of these items were measured on 7-point scales. Additionally, an IMC (Oppenheimer et al., 2009) was included in a short text that introduced the demographic questions, to detect participants who were not following the instructions. The text instructed participants to ignore the first question, which was about political parties, and instead to mark the "Other" box and write "I read the instructions". Religiosity and belief in complementary or alternative medicine (CAM) were measured using a discrete (yes/no) response. Finally, age, gender and education were asked. For the complete wording of all the questions, see the online supplemental material. Not all variables were included in the analyses, because they were not of direct interest to the current research. Some background variables (e.g. trust) were measured because they could be relevant to compare the current research to existing research (e.g. Nyhan, Reifler, Richey, & Freed, 2014), others (e.g. OMC) were measured because they could provide useful insight for future research on correcting misperceptions. All data are available on the OSF (https://bit.ly/2Pv1mlY).

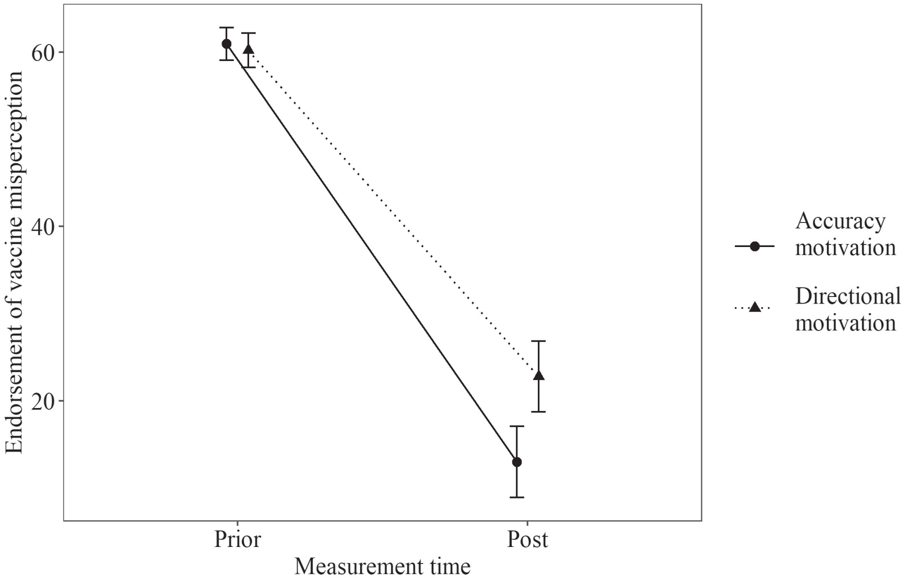
Data analysis. One analysis was conducted to test both hypotheses simultaneously: an ANCOVA with posterior belief as the dependent variable and motivation condition as the independent variable, prior belief certainty as continuous predictor, including the interaction term between prior belief certainty and motivation condition. The first hypothesis regarded the main effect of motivation on posterior endorsement of the misperception, the second regarded the interaction between motivation and prior belief certainty. In the confirmatory analyses, complementary BF are reported.

Results

Manipulation check. Two one-tailed, independent samples t-tests were conducted to test whether the motivation manipulation had the expected effect on participants' motivation in reasoning about the corrective information. As expected, participants in the directional condition (M = 5.38, SD = 1.06) scored significantly higher on the questions measuring directional motivation than participants in the accuracy condition (M = 4.96, SD = 1.18), $t(369.75) = 3.57$, $p < .001$, $d = 0.37$, 95% CI [0.16, 0.58]. Also as expected, participants in the accuracy condition (M = 5.61, SD = 1.02) scored significantly higher on the questions measuring accuracy motivation than participants in the directional condition (M = 5.04, SD = 1.22), $t(348.47) = 4.86$, $p < .001$, $d = 0.51$, 95% CI [0.30, 0.72].

Confirmatory analyses. In support of the first hypothesis, the main effect of motivation condition on posterior endorsement of the misperception while controlling for prior belief certainty was significant, $F(1, 368) = 4.01$, $p = .046$, $\eta_p^2 = .011$, 90% CI [.000, .035], $BF_{01} = 0.79$. Posterior endorsement of the misperception was significantly lower in the accuracy condition ($M = 12.98$, $SD = 56.86$) than in the directional condition ($M = 22.77$, $SD = 54.39$), indicating that the corrective science communication message was more effective for accuracy-motivated participants than directionally motivated participants. See Figure 1 for the prior and posterior scores per motivation condition. The interaction effect between prior belief certainty and motivation condition was not statistically significant ($p = .408$, $BF_{01} = 0.16$), meaning that the effect of motivation on posterior endorsement of the misperception was not moderated by prior belief certainty. Thus, the second hypothesis was not supported.

Figure 1 Prior and Posterior Endorsement of the Vaccine Misperception Separated by Motivation Condition



Note. Error bars indicate standard errors of the mean.

Analysis of the standardized residuals of the ANCOVA model indicated that four observations were classified as model-outliers at > 3 *SD*. Further investigation showed that these four participants all changed their belief in the most extreme way possible; from 100 to -100. Although not preregistered, another ANCOVA was conducted to examine the effect of these four observations on the results. This second ANCOVA, excluding the four model-outliers, also yielded a significant main effect of motivation condition on posterior endorsement of the misperception after controlling for prior belief certainty,

$F(1, 364) = 6.20$, $p = .013$, $\eta_p^2 = .017$, 90% CI [.002, .045], $BF_{01} = 2.22$. Again, the interaction effect was not statistically significant ($p = .771$, $BF_{01} = 0.11$).

Exploratory analyses. In addition to the hypotheses tests, exploratory analyses were conducted. In all of these analyses, model-outliers based on standardized residuals > 3 *SD* were removed from the model. For the complete (preregistered) exploratory analyses, see the online supplemental material.

The first of the exploratory analyses was similar to the main analysis, but included all participants, not just those who participated after the updated preregistration. The ANCOVA indicated that the main effect of motivation condition on posterior endorsement of the misperception found in the main analysis was again significant when all observations were included, $F(1, 397) = 8.88$, $p = .003$, $\eta_p^2 = .022$, 90% CI [.004, .051].

Second, we explored differences between the two conditions on policy support for vaccination and intention to vaccinate. Two ANCOVAs, with motivation condition as the independent variable, policy support or intention as the dependent variable, and controlling for prior belief certainty, yielded no significant effect of motivation condition (both $p > .09$).

Discussion

Experiment 1 provided support for a causal effect of motivated reasoning on the effectiveness of correcting a vaccine-related misperception. In the face of a corrective science communication message, directional motivated reasoning made participants stick to a misperception more than accuracy motivated reasoning. Contrary to our expectations, the influence of motivation on the effectiveness of the correction was not moderated by certainty of the prior belief. Motivation seems to play a role in the effectiveness of a corrective message, regardless of how certain an individual was of a misperception. Exploratory analyses indicated that there was no effect of motivation on support for policy aimed at increasing vaccination or intention to vaccinate.

This experiment is the first to demonstrate a causal role of motivated reasoning in sticking to misperceptions in the face of corrective information. However, there are two limitations. First, the design of the experiment did not allow us to draw conclusions about the effectiveness of inducing accuracy motivation in correcting misperceptions because we could only compare the accuracy condition to the directional condition. It was unclear whether accuracy motivation would increase the effectiveness of the correction compared to a more natural (no motivational instructions) situation. Second, this experiment addressed one topic: vaccination. It was unclear whether the results would generalize to other topics. Both limitations were addressed in Experiment 2.

Experiment 2 – Food Safety

In the second experiment, a food-related misperception was corrected and a control condition was added. First, as in Experiment 1, we expected that inducing accuracy motivation would lead to lower posterior endorsement of the misperception than inducing directional motivation, while controlling for prior belief certainty.

Hypothesis 1: Inducing accuracy motivation will lead to lower posterior endorsement of the misperception than inducing directional motivation, while controlling for prior belief certainty.

Second, research on motivated reasoning has shown that directional reasoning is likely to be the default reasoning style in information processing (Nyhan & Reifler, 2019). Therefore, we expected that inducing accuracy motivation would lead to lower posterior endorsement of the misperception than not inducing any motivation, while controlling for prior belief certainty.

Hypothesis 2: Inducing accuracy motivation will lead to lower posterior endorsement of the misperception than not inducing any motivation, while controlling for prior belief certainty.

The second hypothesis from Experiment 1, regarding the interaction between motivation and prior belief certainty, was dropped because of a lack of support for this hypothesis in Experiment 1

Method

The setup was similar to that of Experiment 1, with the addition of a control condition in which we did not manipulate participants' motivation in reasoning about the corrective message. Furthermore, the IMC was replaced by an instructed-response item (see Materials and Procedure). Just as Experiment 1, the experiment was preregistered on the OSF (https://bit.ly/2Ryop21) and all data and the R script for the analysis can be found on the project page on the OSF (https://bit.ly/2Pv1mlY).

Participants and design. Again, participants were screened prior to participating in the experiment. We selected only those that indicated the statement "Food additives indicated with an E number are unsafe to consume" was true. Following a Bayesian sequential sampling procedure with optional stopping and maximum *N* (Schönbrodt et al., 2017), 1,142 participants (UK nationals) were recruited. As in Experiment 1, they each received £0.85 for participating in the experiment. Again, we checked the BF at predetermined intervals during the sequential sampling procedure. We started checking the BF for the hypothesized effect when 50% of the maximum number of participants completed the experiment and continued to check it after every set of 111 (10% of max sample) new participants. If the BF for both the accuracy-directional contrast and the accuracy-default contrast indicated there was strong evidence (0.1 > BF_{01} > 10; Schönbrodt et al., 2017), data collection would be stopped. Since this was never the case, data collection continued until the maximum *N* of 1,114 participants, which yielded ~0.95 power to replicate the main effect of Experiment 1 (η_p^2 = .022) with alpha = .05 and a successful screening rate of ~75% (Faul et al., 2009).

We collected data from a total of 1,142 participants, because 21 failed an attention check, five did not meet the inclusion criterion related to nationality, and one completed the experiment too fast. In accordance with the preregistration, these participants were excluded from the analyses. Of the remaining 1,115 participants (one more than planned), 854 (76.59 %) indicated that they endorsed the misperception at the beginning of the experiment. Finally and just as in Experiment 1, two participants who did not understand the misperception measure were identified post-hoc and removed from the data. This resulted in 852 participants (596 female, 253 male, two non-binary, one unidentified, M_{Age} = 35.27, SD_{Age} = 12.29) in the total dataset.

The experiment consisted of a one-factor (motivation in reasoning) between-subjects design with three conditions. The directional motivation and accuracy motivation conditions (*n* = 285 and *n* = 277, respectively) were the same as in Experiment 1. We added a ‘default' motivation condition (*n* = 290), in which we did not manipulate participants' motivation.

Materials and Procedure. The procedure was similar to that of Experiment 1. The instructions in the default condition (17 words) were to read the text like one normally would. In contrast to the other two conditions, no time restrictions were applied to reading the instructions and the next-button did not include any text. The corrective science communication message (362 words) was based on information from the Food Standards Agency (Food Standards Agency, 2018) and an article published in Food Quality and Preference (Bearth et al., 2014). The text explained that food additives indicated with E numbers are safe to consume, that an E number actually means that the additive passed safety tests, a short background about food additives, and how an E number is assigned to an additive. An edited graphic about the development of E numbers from The Netherlands Nutrition Centre (The Netherlands Nutrition Centre, n.d.) was included in the text (see Appendix B for the full message).

The IMC was replaced by an instructed-response item, which was placed in the OMC scale. Instructed-response items are useful to identify careless responding (Meade & Craig, 2012). The statement read “To demonstrate you are paying attention, please answer “2” ”.

Measures. The measures were the same as in Experiment 1, but edited to reflect the topic at hand. We added a question measuring participants' belief that what is natural is good, measured by agreement with the statement “In general, I consider what is natural to be good" on a 7-point scale from *Strongly disagree* to *Strongly agree*. In addition, we asked them to report their nationality, as a means of checking the screening criterion for nationality. For the complete wording of all the questions, see the online supplemental material.

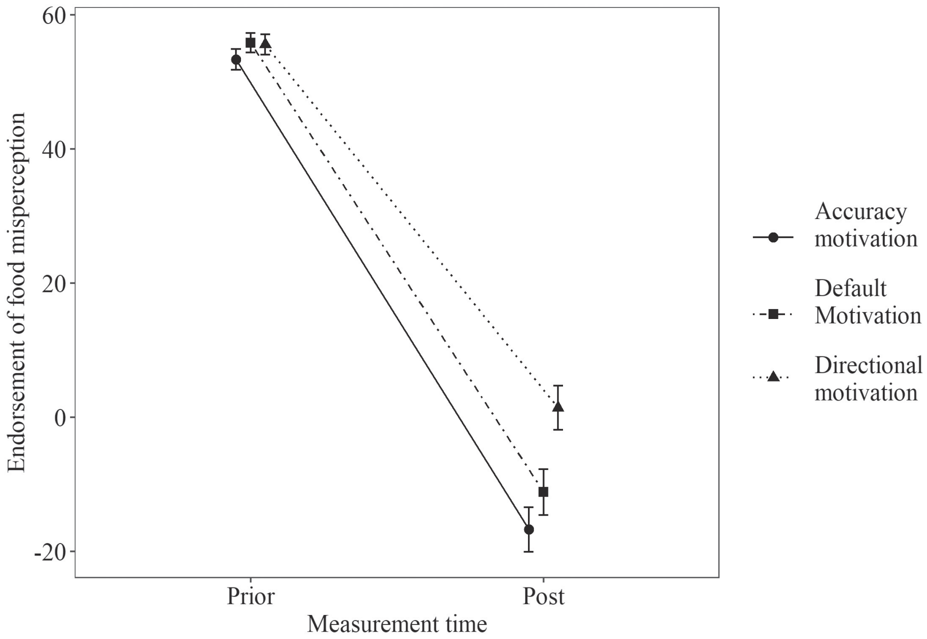
Data analysis. Both hypotheses were tested by conducting an ANCOVA with posterior belief as the dependent variable, condition as the independent variable, and prior belief certainty as continuous predictor. The first hypothesis, comparing accuracy motivation to directional motivation, was tested with the subsample of participants in the accuracy and directional conditions (n = 562). The second hypothesis, comparing accuracy motivation to the default motivation, was tested with a subsample of participants in the accuracy and default conditions (n = 567). Again, BF are reported in the confirmatory analyses.

Results

Manipulation check. Similar to Experiment 1, one-tailed, independent samples t-tests were conducted to test whether the motivation manipulation had the expected effect on participants' motivation in reasoning about the corrective text. As expected, on the questions measuring accuracy motivation participants in the accuracy condition (M = 5.50, SD = 1.00) scored significantly higher than participants in the directional condition (M = 4.93, SD = 1.16), t(552.49) = 6.29, p < .001, d = 0.53, 95% CI [0.36, 0.70], and the default condition (M = 5.00, SD = 0.96), t(560.75) = 6.07, p < .001, d = 0.51, 95% CI [0.34, 0.68]. Also as expected, on the questions measuring directional motivation participants in the directional condition (M = 5.06, SD = 1.14) scored significantly higher than participants in the accuracy condition (M = 4.47, SD = 1.20), t(556.57) = 5.96, p < .001, d = 0.50, 95% CI [0.33, 0.67], and the default condition (M = 4.67, SD = 1.09), t(571.05) = 4.18, p < .001, d = 0.35, 95% CI [0.18, 0.51].

Confirmatory analyses. Replicating the results from Experiment 1 and supporting the first hypothesis, the main effect of motivation condition on posterior endorsement of the misperception, comparing the accuracy and directional conditions, was significant, F(1, 559) = 14.11, p < .001, η_p^2 = .025, 90% CI [.008, .050], BF_{01} = 83.59. Posterior endorsement of the misperception was lower in the accuracy condition (M = -16.71, SD = 55.21) than in the directional condition (M = 1.44, SD = 55.41), again indicating that the corrective science communication message was more effective for accuracy-motivated participants than directionally motivated participants. Contrary to the second hypothesis, comparing the accuracy condition to the default condition yielded no significant effect of motivation (p = .397, BF_{01} = 0.13), indicating that participants that did not receive motivation instructions were just as receptive to the corrective message as accuracy-motivated participants. See Figure 2 for prior and posterior belief scores per condition.

Figure 2 Prior and Posterior Endorsement of the Food Misperception Separated by Motivation Condition



Note. Error bars indicate standard errors of the mean.

Exploratory analyses. Again, in all these analyses, model-outliers based on standardized residuals > 3 *SD* were removed from the model. The complete (preregistered) exploratory analyses can be found in the online supplemental material.

First, also as per the preregistration, we explored the remaining contrast by comparing posterior endorsement of the misperception in the directional condition to the default condition (n = 575). An ANCOVA, similar to the main analysis, indicated that participants in the default condition (M = -11.12, SD = 58.11) displayed significantly lower posterior endorsement of the misperception than participants in the directional condition (M = 1.44, SD = 55.41), $F(1, 572) = 8.15$, $p = .004$, $\eta_p^2 = .014$, 90% CI [.003, .034], indicating that participants who did not receive motivation instructions were more receptive to the corrective message than participants with a directional motivation.

Second, we explored differences between the accuracy and the directional conditions on (1) support for policy aimed at reducing the use of E numbers in food products and (2) intention to avoid the consumption of food products with E numbers in them. Both ANCOVAs, with condition as the independent variable, policy support or intention as the dependent variable, and controlling for prior belief certainty, yielded a significant effect of motivation condition. Regarding policy against E numbers, participants in the accuracy condition (M = 4.81, SD = 1.51) scored significantly lower than participants in the directional condition (M = 5.30, SD = 1.52), $F(1, 559) = 13.60$, $p < .001$, $\eta_p^2 = .024$, 90% CI [.007, .048]. Mediation analysis using bootstrapping procedures (N = 10.000; Imai, Keele, & Tingley, 2010) indicated that this effect was mediated by posterior endorsement of the misperception ($\beta = 0.24$, 95% CI [0.11, 0.37], $p < .001$). Of the total effect of motivation on policy support, 52.62% was explained by posterior endorsement of the misperception, leaving a marginally significant average direct effect ($\beta = 0.21$, 95% CI [< 0.00, 0.42], $p = .052$). Similarly, regarding intention to avoid E numbers, participants in the accuracy condition (M = 3.86, SD = 1.55) scored significantly lower than participants in the directional condition (M = 4.21, SD = 1.56), $F(1, 559) = 6.17$, $p = .013$, $\eta_p^2 = .011$, 90% CI [.001, .030]. This effect was also mediated by posterior endorsement of the misperception ($\beta = 0.27$, 95% CI [0.12, 0.41], $p < .001$). Of the total effect of motivation on intention to avoid E numbers, 78.93% was explained by posterior endorsement of the misperception, leaving a nonsignificant average direct effect ($p = .509$). These results demonstrate that the effect of motivation is not limited to the misperception.

Finally, we explored the hypothesized interaction effect between prior belief certainty and motivation condition from Experiment 1. We conducted the same ANCOVA as in Experiment 1 with only the accuracy and directional conditions. Again, the ANCOVA yielded a nonsignificant interaction effect ($p = .430$), meaning that the effect of motivation on posterior endorsement of the misperception was not moderated by prior belief certainty.

Discussion

Experiment 2 replicated and extended the findings from Experiment 1. Again, we found support for a causal role of motivated reasoning in the effectiveness of correcting a misperception, this time for a misperception related to food safety, thereby supporting the generalizability of these results. Contrary to our expectations, we did not find that inducing accuracy motivation strengthened the corrective effect of the science communication message compared to the default motivation. Instead, exploratory analyses indicated that the default motivation lead to lower posterior endorsement of the misperception than directional motivation. In contrast to Experiment 1, the results indicated that the effect of motivation on posterior endorsement of the misperception was reflected in a difference in policy support and intention. Accuracy-motivated participants reported lower support for policy aimed at reducing the use of E numbers in food products and intention to avoid the consumption of food products with E numbers in them than directionally motivated participants. This difference was (partly) explained by the change in endorsement of the misperception.

General Discussion

The current research investigated the role of motivated reasoning in the effectiveness of correcting misperceptions about scientific facts. We found evidence for a causal role of motivated reasoning in the effectiveness of corrections, such that individuals who were driven by accuracy motivation were more receptive to the corrective information than individuals driven by directional motivation. Contrary to what we expected, the effect of motivation was not moderated by prior belief certainty. Whether in great doubt or very certain, motivation in reasoning about corrective information seems to affect how amenable one is to this information. Also contrary to our expectations, we found that in the case of a food-related misperception, individuals' default motivation made them just as receptive to the corrective information as accuracy motivation. Directional reasoning made individuals stick to the misperception more than accuracy-driven reasoning or default reasoning. Finally, our findings demonstrated that the influence of motivation was not limited to the misperception itself. Specifically, the difference in posterior endorsement of the misperception between accuracy and directionally motivated individuals was reflected in second order outcomes: support for policy aimed at reducing E numbers in food products and intention to consume less E numbers were lower among accuracy motivated individuals than among directional motivated individuals. This was not the case for Experiment 1, which might be explained by lower power as well as the fact that the average correction was larger in Experiment 2 than in Experiment 1.

These findings are cause for a more optimistic view of human receptivity to science communication than often found in the literature. Although we did find that directional reasoning might reduce the corrective effect of a science communication message, we found no evidence for the prevailing assumption in research on motivated reasoning that corrections often backfire (see P. S. Hart & Nisbet, 2012; Nyhan et al., 2013; Nyhan & Reifler, 2010; Zhou, 2016). There has been some debate about this backfire effect (Druckman & McGrath, 2019). In line with other research (Garrett et al., 2013; Guess & Coppock, 2018; Hill, 2017; van der Linden et al., 2018; Wood & Porter, 2019), we found no evidence of such a polarizing effect of our science communication message. To the contrary, our findings demonstrated that individuals are not automatically predisposed to defend their prior beliefs in the face of corrective information. Only when we induced a directional motivation did participants stick to the misperception more than participants would by default. Moreover, even individuals who were induced to have a directional motivation on average reduced their endorsement of the misperception, rather than increasing it.

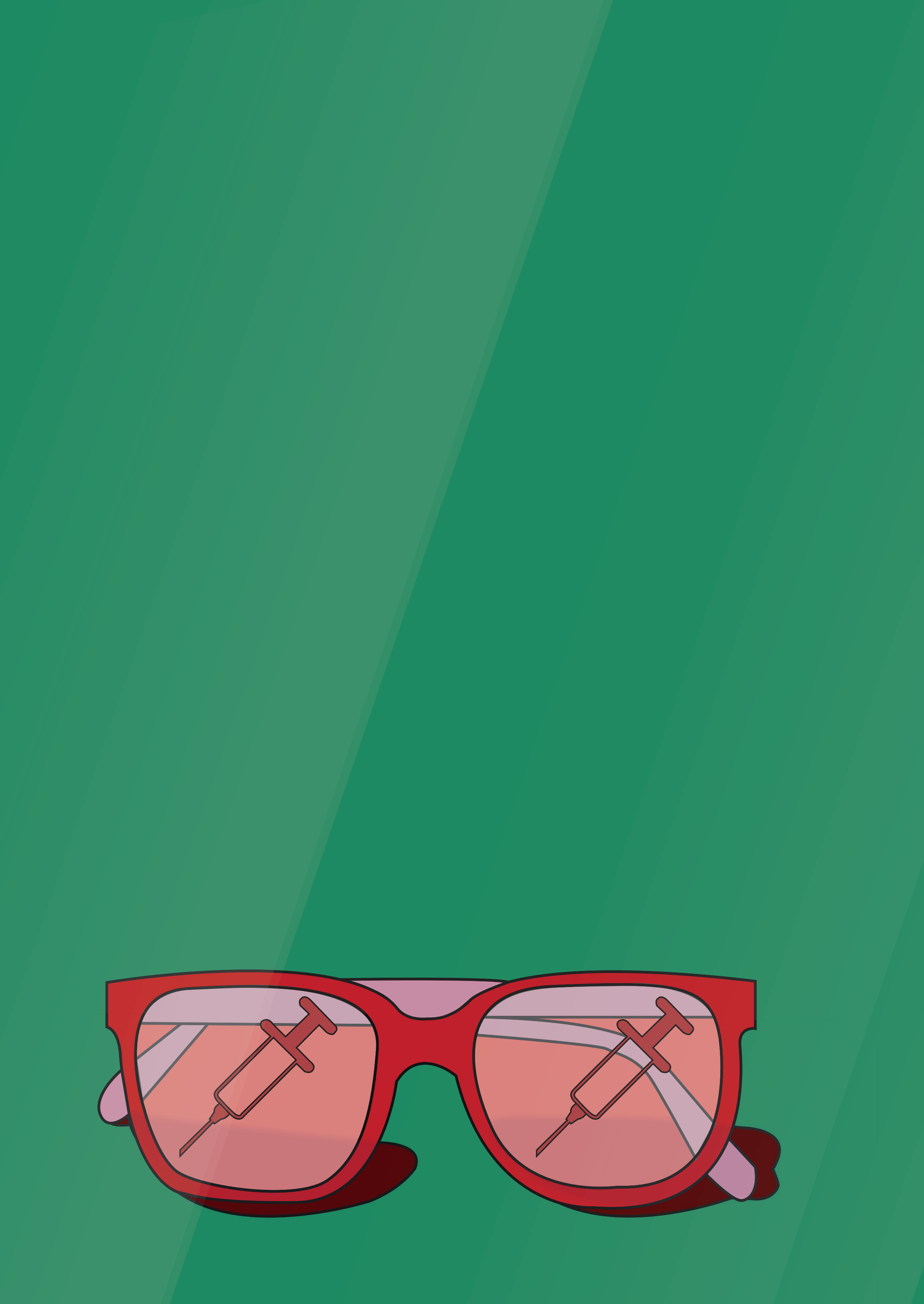
How can these contrasting findings be explained? As suggested in the original work on motivated reasoning by Kunda (1990), the influence of directional reasoning is limited by people's perceptions of reality and plausibility. Clear, one-sided information regarding factual beliefs is unlikely to lead to backfire effects (Flynn et al., 2017). In line with this, research demonstrates that biased updating requires, in addition to motivation, at least some level of ambiguity or balance in the information (Dixon et al., 2015; Dixon & Clarke, 2013; Sharot & Garrett, 2016) or should concern "softer" outcomes such as candidate favorability (Nyhan et al., 2020). Instead of backfiring, corrective information can be very effective if it "hits [people] between the eyes" (Kuklinski et al., 2000). In line with this idea, our message directly and very specifically contradicted the misperception. The current research demonstrated that a clear corrective message regarding a factual belief is likely to be effective in correcting misperceptions.

The current study provided the first step in investigating the causal role of motivated reasoning in sticking to misperceptions and in finding out whether this role is similar for different contentious issues (i.e., vaccine and food safety). There are, however, some limitations. First, because of demand characteristics in the motivation manipulation, part of the difference in posterior belief between the experimental conditions might be a result of response bias. Participants may have chosen to satisfy the researcher's expectation, thereby biasing the main results of the experiments. As with most research relying on self-report measures, this cannot be ruled out completely (though see Mummolo & Peterson, 2019). However, we have reason to believe that demand characteristics do not explain the current findings. Participants were told, upon measure of their posterior endorsement of the misperception, that we were interested in their judgment and that this was not a test. If anything, a participant motivated to satisfy the researcher should in this case answer as honestly as possible. Furthermore, Prolific is known as a platform that treats their participants fairly. Participants knew that they would be paid for participating in research, regardless of whether they satisfied the researchers. Finally, there was no interaction between participant and researcher in the experiments, which would further reduce demand characteristics.

Then there are a number of smaller limitations. The first considers the ecological validity of our motivation manipulation. We simply asked participants to process the information in such a way that it resembled either accuracy or directional motivated reasoning. This is not a real-life situation. Future research could make the motivation manipulation more ecologically valid, for instance by investigating an appeal to accuracy motivation as part of the corrective message or by investigating directional motivation primes in a more complex information environment. Second, in the design of the current experiments we assumed that participants would be exposed to corrective information. However, a part of motivated reasoning is motivated selection of information (Knobloch-Westerwick & Jingbo Meng, 2009). In research that manipulated motivation in information selection, researchers found different preferences for information as a product of accuracy motivation and defense motivation (similar to directional motivation; Winter, Metzger, & Flanagin, 2016). Although the debate on selective exposure is far from settled (cf. Garrett, 2009), the first challenge is to get people to read corrective information. The current research provides information only on what happens when this exposure is achieved in the first place.

The current study gives lead to some directions for future research. First, regarding the development of an intervention fostering accuracy motivation, it would be valuable to know which part of the motivation manipulation led to a difference in the corrective effect of the message. Was it being even-handed, considering the opposite view (also see Lord, Lepper, & Preston, 1984), looking for disconfirmation, or a combination of all of those things? Second, a test of the 'between the eyes'-effect of a correction would provide more insight into the conditions of belief polarization. Including both an ambiguous and clear correction in a paradigm such as the one we used should be of great interest for the debate on backfire and boomerang effects. Finally, research on motivated reasoning could benefit from a measure of the type of motivation in reasoning. Currently, indicators of motivation such as political ideology and worldview are often used. These indirect measures are useful, but a direct measure of motivation should be more valuable. Ideally, this measure could also be used to investigate individuals' default response to different types of information, potentially uncovering a motivated reasoning 'trait'.

Misperceptions can cause serious problems. This research focused on vaccine and food safety, but the results are expected to also apply to other hotly debated topics, such as climate change, gun control, or genetic modification of food. If there is a motive to hold on to a misperception, it will play an important role in correcting misperceptions. At the same time, this research supports an optimistic view of people's receptivity to science communication. By default, we are open to new information and are likely to change our beliefs when information leads us to.



CHAPTER 3

Scientific Consensus Communication About Contested Science: A Preregistered Meta-analysis

This chapter is in press as:
van Stekelenburg, A., Schaap, G., Veling, H., van 't Riet, J., & Buijzen, M. (in press). Scientific consensus communication about contested science: A preregistered meta-analysis. *Psychological Science*

Abstract

Scientific consensus communication is among the most promising interventions to minimize the gap between experts' and the public's belief in scientific facts. There is, however, discussion about its effectiveness in changing consensus perceptions and beliefs about contested science topics. This preregistered meta-analysis assessed the effects of communicating the existence of scientific consensus on perceived scientific consensus and belief in scientific facts. Combining 43 experiments about climate change, genetically modified food, and vaccination, we show that single exposure to consensus messaging has a positive effect on perceived scientific consensus (g = 0.55) and on factual beliefs (g = 0.12). Consensus communication yielded very similar effects for climate change and genetically modified food, while the low number of experiments about vaccination prevented conclusions regarding this topic specifically. Although the effect is small, communicating scientific consensus appears to be an effective way to change factual beliefs about contested science topics.

Keywords: belief, scientific facts, scientific consensus, science communication, meta-analysis, climate change, genetically modified food, vaccination, open data, preregistration

Scientific Consensus Communication About Contested Science: A Preregistered Meta-analysis

We are facing a number of formidable challenges: The planet is warming, with a rising sea level and more extreme weather events such as floods and extreme heat causing a public health crisis (IPCC, 2018). A substantial proportion of the global population is facing undernourishment (United Nations, n.d.). While safe and effective genetic engineering technology could at least partially alleviate this problem, this technology is restricted in many countries and food products that result from this technology are unwanted by substantial parts of the public (Scott et al., 2018). And even when safe and effective vaccines are available, a considerable part of many nations' citizens is hesitant to take them up (Larson et al., 2016).

These issues – climate change, genetically modified food, and vaccination – have at least one thing in common: they are highly contested topics among parts of the general public despite clear scientific evidence, as reflected in strong scientific consensus. Inaccurate beliefs about these topics can have detrimental effects on tackling the challenges that we face. For instance, climate change belief is an important predictor of the intention to behave in climate-friendly ways (Hornsey et al., 2016), perceived benefit and perceived risk are important predictors of acceptance of gene editing technology (Siegrist, 2000), and the perception of adverse effects of vaccines is an important factor in vaccine uptake (Smith et al., 2017). Additionally, any democracy benefits from having an informed electorate.

To help the public understand the scientific facts surrounding these topics, science communication strategies may play an important role. One easy to implement and often studied science communication intervention to close the gap between scientific facts and the public's belief in these scientific facts relies on communicating the scientific consensus, a high degree of agreement among scientists (van der Linden, 2021). In addition to providing people with an inherently valuable piece of information, the strategy of communicating scientific consensus relies on two heuristics: trust in experts and the idea that consensus implies correctness (van der Linden, 2021). When people are not aware of the scientific consensus, communicating consensus may lead to an updated estimate of the scientific consensus, which in turn will act as a gateway to personal factual beliefs (Lewandowsky, Gignac, & Vaughan, 2013). This reasoning is captured in the 'gateway belief model' (van der Linden, Leiserowitz, et al., 2015, 2019). The gateway belief model is supported by a number of studies demonstrating that communicating the existence of scientific consensus can be an effective strategy to elicit accurate perceptions of scientific consensus (i.e., people's estimate of the degree of consensus among scientists), even on controversial issues like climate change, genetically modified food, and vaccination (Goldberg, van der Linden, Ballew, Rosenthal,

& Leiserowitz, 2019; Kerr & Wilson, 2018; Lewandowsky, Gignac, & Vaughan, 2013; van der Linden, Clarke, et al., 2015; van der Linden, Leiserowitz, et al., 2019).

However, there is also conflicting evidence, leading to discussion about the effectiveness of consensus communication as a science communication strategy (Bayes et al., 2020; Landrum & Slater, 2020; van der Linden, 2021). Some scholars argue that people might not see experts who adopt positions incongruent with their preferences as knowledgeable or trustworthy (Kahan et al., 2011) or that people might experience reactance from being exposed to a scientific consensus message (Ma et al., 2019; also see Dixon et al., 2019; van der Linden, Maibach, et al., 2019). Others argue that even if the scientific consensus itself is accepted by individuals, this may not necessarily cause them to change their personal beliefs (Bolsen & Druckman, 2018; Dixon, 2016; Pasek, 2018). These arguments may be especially applicable to contested science topics, such as climate change, where trust in scientists is relatively low compared to other scientists and personal beliefs are fairly stable (e.g., Pew Research Center, 2016). Thus, there is debate about the effectiveness of scientific consensus messaging in informing the public and it is unclear if the effects of such messages differ by topic.

The current meta-analysis contributes to the debate by meta-analytically testing the effects of scientific consensus communication related to informing the public. The main objective was to assess the effects on 1) perceived scientific consensus and 2) belief in scientific facts regarding contested science topics. We focus on the three aforementioned topics, because they are contested topics among substantial parts of the public (e.g., Larson et al., 2016; Leiserowitz et al., 2021; Scott et al., 2018) and because we expected there to be multiple studies per topic to meta-analytically synthesize. To assess these effects, only randomized experiments were included in the meta-analysis. In line with the gateway belief model, we hypothesized that exposure to a message conveying scientific consensus would lead to a higher estimate of scientific consensus than not being exposed to such a message. Similarly, we hypothesized that those individuals exposed to a message conveying scientific consensus would change their beliefs to be more in line with the scientific consensus than those individuals not exposed to such a message. Furthermore, we aimed to investigate if the effectiveness of consensus communication differs by topic, but had no a priori hypotheses regarding such differences.

In addition to comparing effects of consensus communication between topic, we conducted sensitivity analyses and examined reporting bias, aiming to provide insight into the robustness of the effects. Finally, we conducted an exploration of other moderators than the contested science topic that might explain the (in)effectiveness of scientific consensus communication. Much discussion about the gateway belief model centers around differential effects of scientific consensus communication for specific groups (e.g., Landrum & Slater, 2020; Ma et al., 2019; van der Linden, Leiserowitz, et al., 2019).

To explore if scientific consensus communication might be more or less effective for certain groups, we examined moderating effects of conservatism and pre-existing perceptions of consensus and beliefs. In the US, where most experiments were conducted, political conservatism is related to skepticism towards science in general and climate science specifically (Azevedo & Jost, 2021; Lewandowsky & Oberauer, 2021; though see Rutjens et al. (2018) for skepticism about genetically modified food). Such a skeptical attitude might make conservatives more likely to distrust scientists and exhibit reactance to scientific consensus messages, or to downgrade the informational value of scientific consensus itself. In contrast, however, some climate change research has found that consensus communication might neutralize the effect of political orientation, increasing climate change acceptance particularly among conservatives (Lewandowsky, Gignac, & Vaughan, 2013; van der Linden, Leiserowitz, et al., 2019). For the same reasons as skepticism related to conservatism, scientific consensus messaging might also not be accepted by people with conflicting pre-existing perceptions of consensus or factual beliefs (Pasek, 2018). But again, this communication strategy may also neutralize such conflicting beliefs (van der Linden, Leiserowitz, et al., 2019). Thus, the potentially moderating roles of conservatism and pre-existing perceptions and beliefs are yet unclear.

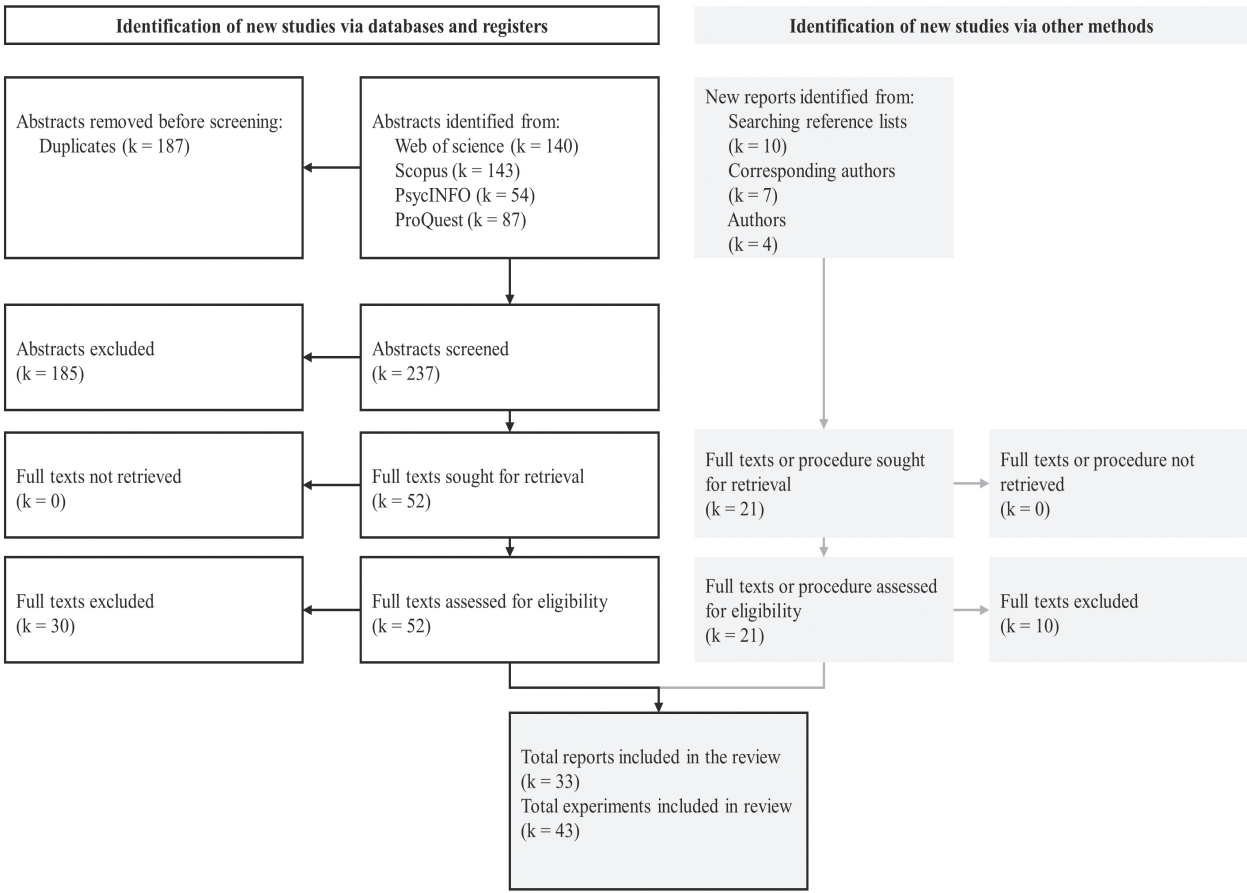
Method

To avoid bias and provide evidence of a priori analysis intentions, which is an important benefit of preregistering meta-analyses (Quintana, 2015), the protocol for this meta-analysis was preregistered on the Open Science Framework (OSF; https://bit.ly/3B-5bCsF, for all deviations from the preregistered protocol, see online Supplemental Material). All confirmatory parts of this work were preregistered. For exploratory parts it is made explicit in the results section whether they were preregistered or not. The data and analysis script (R) are available on the OSF (https://bit.ly/3JaOdZC). The reporting of this meta-analysis was guided by the standards of the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) Statement (Page, McKenzie, et al., 2021).

Literature Search

We searched for published and unpublished articles in three ways: 1) we searched electronic databases, 2) we examined the reference lists of the articles that met the inclusion and exclusion criteria, and 3) we contacted corresponding authors of included articles to ask for other relevant work. See Figure 1 for a flow diagram describing the literature search process.

Figure 1 Flow Diagram of Literature Search



First, we searched electronic databases Web of Science, Scopus, PsycINFO, and ProQuest. We used sets of keywords to search for experiments investigating scientific consensus and a belief about one of the three contested science topics (see Table 1). This search took place March 15, 2021. All search results (k = 424) were imported in the Rayyan web application (Ouzzani et al., 2016), where duplicates (k = 187) were removed. Two coders then reviewed all abstracts to indicate whether the article contained any relevant experiments (~93% agreement, Krippendorf's α = 0.79). Discrepancies between the two coders were resolved through discussion. The following inclusion criteria were used to screen abstracts:

1. The article should report an experiment with a between-subjects manipulation of scientific consensus communication; information about scientific consensus provided vs. control (no information about scientific consensus).
2. The topic of consensus communication of the experiment(s) of interest should be climate change, vaccination, or genetically modified food.
3. One of the dependent variables of the experiment(s) of interest should be a measure of perceived scientific consensus related to the consensus message or a measure of participants' belief in a factual statement.
4. The participant sample of the experiment(s) of interest should consist of an adult human population.
5. The article should be written in English.

Table 1. Keywords for literature search. Articles needed to mention at least one term from each column in the title, abstract, or keywords to be screened for inclusion. Additionally, we limited the search to articles in English. Finally, for ProQuest we limited the search to 'Scholarly Journals or Dissertations & Theses', to exclude non-scientific sources such as newspaper or magazine articles.

Experiment	Consensus	Belief	Contested science
experiment*	scien* consensus	belief	climate change
interven*	expert consensus	perception	climate emergency
rct	perc* consensus	misperception	climate crisis
random* control* trial*	estim* consensus	conception	global warming
test	accept* consensus	misconception	global heating
effect	scien* agree*	understanding	vaccin*
manipulat*	expert* agree*	misunderstanding	immuniz*
	perc* agree*	fact	inocul*
	estim* agree*		genetic* modified
	gateway belief		genetic* engineered
			GMO
			GM food

Once all abstracts were screened, full texts of the remaining records (k = 52) were obtained. Two full texts were not publicly available and were successfully requested from the relevant corresponding authors. All full texts were reviewed by two coders (~92% agreement, Krippendorf's $\alpha = 0.88$) on the following exclusion criteria:

1. Participants' belief in the factual statement of interest should not have been manipulated with misinformation in addition to the experimental manipulation of interest (e.g., exposing participants to misinformation before or after a consensus message).
2. The article should report original data not reported elsewhere.
3. The experiment(s) of interest should adhere to the inclusion criteria that were used to screen the abstracts.

If an article did not adhere to these criteria, the full text (or relevant experiment in the full text) was excluded from the meta-analysis.

After having screened abstracts for inclusion and full texts for exclusion criteria, the reference lists of the remaining articles (k = 22) were searched for other relevant articles. Full texts of new, potentially relevant articles were assessed for eligibility (k = 10) using the same criteria as for the original find and added to the list if screening by two independent coders (100% agreement) was passed. For those new articles added to the list (k = 3), the reference list was searched as well, which led to no new potentially relevant articles.

Finally, in May and June 2021, we contacted corresponding authors of articles in the list ($N = 18$) and asked them to bring any relevant work that was missing to our attention. We also considered if we had encountered any missing relevant work ourselves. All new articles (or procedures of experiments, where no manuscript was available; k = 11) were screened using the same inclusion and exclusion criteria (100% agreement between two coders). This yielded eight new unpublished articles. Adding these and the three articles from the reference list search to articles from the database search resulted in a total of 33 articles containing 43 experiments that were included in this meta-analysis.

Extracting Data

Relevant data were extracted from the final list of included experiments by the first author. The preregistered protocol included a data extraction procedure for effect size data, describing how to handle situations such as multiple consensus messaging conditions and multiple dependent variables. We focused on immediate effects of consensus communication and included studies both with passive and active control conditions (e.g., reading a mock news article about the relevant topic without consensus information). With regard to the outcome measures, we extracted post-manipulation information related to perceptions of scientific consensus and belief in scientific facts that were specifically addressed in the consensus message. Thus, all designs were treated as between-subjects posttest designs. Meta-analysis using standardized mean differences (such as Hedge's *g*) does not allow combining effect sizes from post-manipulation scores with effect sizes from difference scores (using both pre- and post-manipulation scores; Deeks et al., 2021). This means that even if the experiment included a pre-manipulation measure of one of our outcomes, this information was not used to calculate the effect size. Pre-manipulation scores were used, however, in the exploratory analyses of pre-existing perceptions of scientific consensus and pre-existing belief in scientific facts.

If an experiment contained multiple between-subjects manipulations of consensus communication (e.g., a condition with a consensus message in text and a condition with a consensus message in a bar chart), these were synthesized to obtain one single comparison to the control group. Messages reporting at least 82% agreement among scientists (based on the lowest percentage of agreement that was considered as 'high consensus' in the included works, Kobayashi, 2018), or simply stating that there is a scientific consensus (e.g., "On GM there is a rock-solid scientific consensus", Hasell et al., 2020) or stating that a large number of scientists are in agreement (e.g., "a recent report produced by 300 expert scientists", Bolsen & Druckman, 2018) were included as scientific consensus conditions. If an experiment contained multiple, unaggregated measures of a factual belief that were used as dependent variables, only the measure that was most specifically related to the consensus message was extracted (e.g., if a consensus message focused on the safety of vaccines, we extracted information related to participants' concerns regarding the safety of vaccines while ignoring a more specific measure of participants' belief in a link between vaccines and autism). If multiple, unaggregated measures of a factual belief were used as dependent variables and multiple of these beliefs were specifically addressed in the consensus message, those measures were aggregated by standardizing them (if they were not measured on the same scale) and taking the mean. For example, if a consensus message focused on both the reality of climate change and its human causation, we extracted information regarding measures of belief in climate change and of belief in its human causation.

Of course, not all situations could be foreseen (e.g., multiple between-subjects control conditions). Therefore, ad hoc decisions had to be made during data extraction when we encountered situations that were not described in the preregistered protocol. A second author independently coded a random sample of five experiments after training, following the same procedure, which yielded the same results. The complete procedure, separating preregistered from ad hoc decisions, can be found in the online Supplemental Material.

For each experiment, means, SDs (or SEs), and sample size per condition (*n*), were extracted. If this information was not available from the article, we requested the missing statistical information from the corresponding author. In all but one case the requested information was obtained (the effect size in question was coded as missing). Means, SDs or SEs, and *n* were used to calculate Hedges' *g*, which was recoded where necessary such that a positive value indicated higher perceived scientific consensus in line with the scientific facts and more scientifically accurate beliefs, compared to control.

As preregistered, we also extracted information describing the contested science topic that the experiment focused on (i.e., climate change, genetically modified food, or vaccination). All other variables that were extracted were done so in a data driven manner. Analyses related to these variables are therefore labelled exploratory. These variables included sample conservatism (if the experiment was conducted in the US, to ensure that conservatism measured more or less the same construct across experiments), pre-existing perceptions of scientific consensus and pre-existing beliefs, and whether the experiment was preregistered. See Table 2 for a list of information that was extracted.

Table 2 Studies and Related Information Included in the Meta-analysis

Article	Study	Topic	Location	Conservatism	Pre-existing consensus perception	Pre-existing belief	Preregistered	Published or accepted	*g* (SE) perceived scientific consensus	*g* (SE) belief in scientific facts
Akerlof (2014)	1	Climate change	US	0.38	0.8	0.73	n	n	0.32 (0.14)	0 (0.14)
Bolsen & Druckman, (2018)	1	Climate change	US	0.48	NA	0.6	n	y	NA	0.14 (0.09)
Bolsen et al. (2014)	2	Climate change	US	0.42	NA	0.68	n	y	NA	0.05 (0.14)
Brewer & McKnight (2017)	1	Climate change	US	0.52	0.77	0.77	n	y	0.44 (0.12)	0.24 (0.12)
Chinn (2020): Chapter 4	1	Climate change	US	0.49	0.67	0.68	n	y	0.79 (0.05)	0.14 (0.04)
Clarke (n.d.)	1	Climate change	US	0.45	0.77	0.82	n	n	0.42 (0.16)	0.21 (0.16)
Cook & Lewandowsky (2016)	1	Climate change	US	NA	0.55	0.63	n	y	1.46 (0.13)	0.19 (0.11)
Cook & Lewandowsky (2016)	2	Climate change	Australia	NA	0.57	0.64	n	y	1.63 (0.12)	0.33 (0.1)
Cook (n.d.)	1	Climate change	US	NA	NA	0.52	n	n	NA	0.02 (0.15)
Deryugina & Shurchkov (n.d.)	1	Climate change	US	0.34	0.78	0.77	n	n	NA	0.23 (0.15)
Deryugina & Shurchkov (2016)	1	Climate change	US	0.54	0.68	0.68	n	y	0.06 (0.06)	0.06 (0.06)
Dixon (2016)	1	GM food	US	NA	0.69	0.53	n	y	0.43 (0.16)	0.1 (0.16)
Dixon (2016)	2	GM food	US	NA	0.65	0.47	n	y	0.74 (0.13)	0.34 (0.13)

Table 2 Continued

Article	Study	Topic	Location	Conservatism	Pre-existing consensus perception	Pre-existing belief	Preregistered	Published or accepted	*g* (SE) perceived scientific consensus	*g* (SE) belief in scientific facts
Dixon et al. (2017)	1	Climate change	US	0.53	NA	0.63	n	y	NA	0.29 (0.08)
Goldberg et al. (2019a)	1	Climate change	US	0.49	0.72	0.69	n	y	0.47 (0.1)	0.07 (0.1)
Goldberg et al. (2019b)	1	Climate change	US	0.37	0.78	0.79	n	y	0.37 (0.07)	0.02 (0.06)
Goldberg et al. (2019b)	2	Climate change	US	0.48	0.71	0.72	n	y	0.63 (0.06)	0.14 (0.06)
Goldberg et al. (2019b)	3	Climate change	US	0.38	0.75	0.71	n	y	0.09 (0.06)	0.02 (0.06)
Goldberg et al. (2019b)	4	Climate change	US	0.38	0.81	0.77	n	y	0.35 (0.06)	0.15 (0.06)
Hasell et al. (2020)	1	GM food	US	0.48	0.57	0.43	n	y	0.25 (0.08)	0.14 (0.08)
Kerr & Wilson (2018)	1	Climate change	New Zealand	NA	0.8	0.74	n	y	0.89 (0.16)	0.03 (0.15)
Kerr & Wilson (2018)	2	GM food	New Zealand	NA	0.58	0.5	n	y	1.43 (0.17)	0.3 (0.16)
Kobayashi (2018)	2	Climate change	Japan	NA	0.6	NA	n	y	-0.01 (0.09)	NA
Kobayashi (2019)	1	GM food	Japan	NA	0.45	0.4	n	y	0.7 (0.07)	0.12 (0.07)
Kotcher et al. (2014)	1	Climate change	US	0.48	0.63	0.71	n	n	0.57 (0.06)	0.16 (0.06)

Table 2 Continued

Article	Study	Topic	Location	Conservatism	Pre-existing consensus perception	Pre-existing belief	Preregistered	Published or accepted	*g* (SE) perceived scientific consensus	*g* (SE) belief in scientific facts
Landrum et al. (2019)	1	GM food	US	0.37	0.6	NA	y	y	0.14 (0.12)	0.19 (0.12)
Lewandowsky et al. (2013)	2	Climate change	Australia	NA	0.67	0.74	n	y	0.94 (0.22)	0.51 (0.21)
Lyons et al. (2021)	1	Vaccination	Spain	NA	0.73	0.76	y	n	0.04 (0.06)	-0.02 (0.06)
Lyons et al. (2021)	2	GM food	Spain	NA	0.5	0.41	y	n	0.08 (0.05)	0.08 (0.05)
Ma et al. (2019)	1	Climate change	US	0.45	NA	0.66	n	y	NA	0.02 (0.1)
Maertens et al. (2020)	1	Climate change	US	0.36	0.85	0.82	y	y	0.64 (0.14)	0.23 (0.13)
Myers et al. (2015)	1	Climate change	US	0.48	0.63	0.7	n	y	0.37 (0.1)	0.05 (0.1)
Myers et al. (2015)	2	Climate change	US	0.47	0.65	0.74	n	y	0.69 (0.08)	0 (0.08)
Rode et al. (2021)	1	Climate change	US	0.31	0.82	0.82	n	y	0.38 (0.1)	0.21 (0.09)
Rode et al. (2021)	2	Climate change	US	0.31	0.88	0.83	n	y	0.29 (0.07)	0.13 (0.07)
Rode et al. (2021)	3	Climate change	US	0.5	0.81	0.68	y	y	0.28 (0.06)	0.02 (0.06)
Tschötschel et al. (2021)	1	Climate change	Germany	NA	0.71	0.77	y	y	0.16 (0.07)	0.01 (0.07)

Table 2 Continued

Article	Study	Topic	Location	Conservatism	Pre-existing consensus perception	Pre-existing belief	Preregistered	Published or accepted	*g* (SE) perceived scientific consensus	*g* (SE) belief in scientific facts
van der Linden, Leiserowitz, et al. (2015)	1	Climate change	US	0.4	0.67	0.68	n	y	0.57 (0.1)	0.09 (0.1)
van der Linden et al. (2017)	1	Climate change	US	0.39	0.71	NA	n	y	0.93 (0.08)	NA
van der Linden, Clarke, et al. (2015)	1	Vaccination	US	0.42	0.84	0.58	n	y	0.6 (0.17)	0.31 (0.17)
van der Linden, Leiserowitz, et al. (2019)	1	Climate change	US	0.46	0.67	0.68	n	y	0.79 (0.03)	0.14 (0.03)
van Stekelenburg et al. (n.d.)	3	GM food	US	0.38	0.46	0.22	y	y	0.77 (0.09)	0.25 (0.08)
Williams & Bond (2020)	1	Climate change	US	0.35	0.83	NA	y	y	0.86 (0.12)	NA

Note. NA = not available. For more information on coding of conservatism, pre-existing consensus perception, and pre-existing belief, see 'Moderators' in the Results section.

Analytic Strategy

The meta-analytic estimates, expressed in Hedges' g and 95% confidence intervals (CIs), of the effect of scientific consensus communication on perceived scientific consensus and beliefs were estimated using random-effects models. We used the restricted maximum likelihood (REML) estimator to estimate τ2 and the Knapp-Hartung-Sidik-Jonkman (KHSJ) method for tests and 95% CIs. The REML estimator performs better than other often used heterogeneity estimators and the KHSJ method outperforms other methods of estimating summary effects and CIs (Langan et al., 2019). To describe between-study heterogeneity, in addition to the estimate of τ2, the Q-test for heterogeneity and the I^2 statistic are reported.

We used the dmetar (Harrer et al., 2019), meta (Balduzzi et al., 2019), and metafor (Viechtbauer, 2010) packages for R.

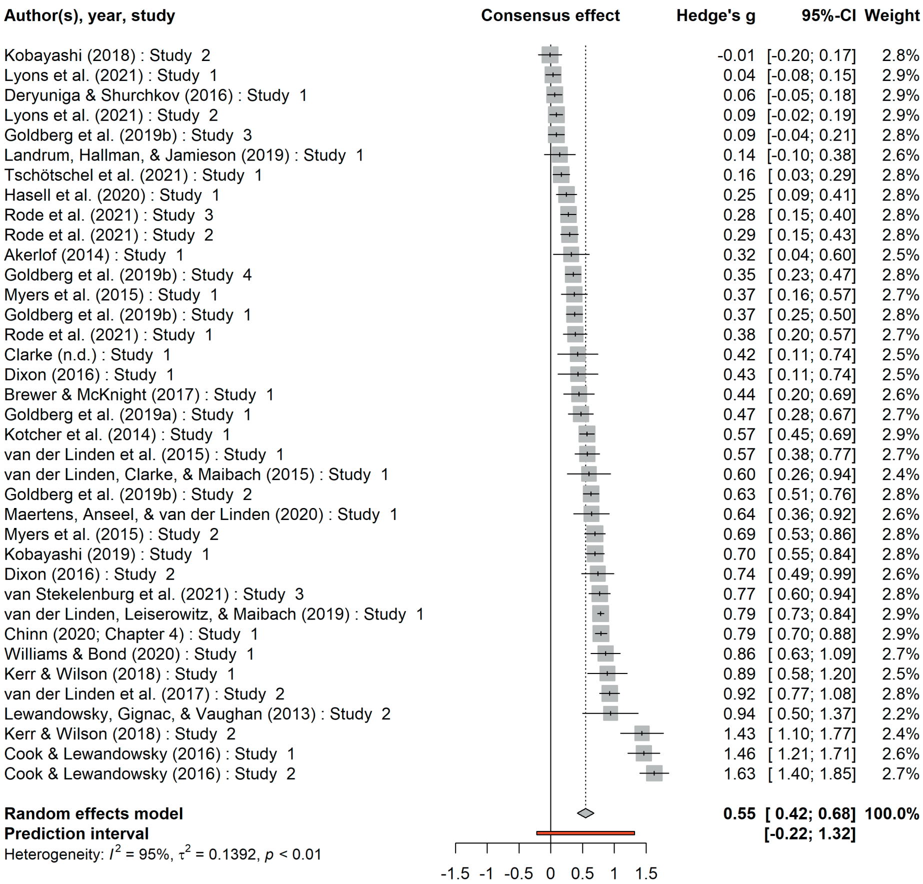
Results

The final set of experiments (k = 43) yielded 37 effect sizes (total N = 32,398) for the effect of scientific consensus communication on perceived scientific consensus and 40 effect sizes (total N = 33,985) for the effect of scientific consensus communication on belief in scientific facts. None of the experiments contributed more than one effect size per outcome. Most experiments investigated scientific consensus communication about climate change (k = 33) or genetically modified food (k = 8), while only two experiments focused on vaccination.

Perceived Scientific Consensus

The estimated average effect size of scientific consensus communication on perceived scientific consensus was g = 0.55 (95% CI: 0.42 to 0.68), which differed significantly from zero, $t(36) = 8.52$, $p < .001$, meaning that a statistically significant meta-analytic effect was identified. Figure 2 shows a forest plot of the observed outcomes and the estimated average effect. Heterogeneity in the effects of scientific consensus communication on perceived scientific consensus between experiments was high, $\tau^2 = 0.139$, $Q(36) = 752.51$, $p < .001$, $I^2 = 95.2\%$ (95% CI: 94.2% to 96.1%). This high heterogeneity suggests that the experiments might not share one common effects size, which is reflected in a quite broad 95% prediction interval ranging from -0.22 to 1.32. Prediction intervals reflect the distribution of true effect sizes in random effects meta-analysis (Borenstein et al., 2009). In contrast to confidence intervals, which describe the range in which the population effect is likely to be found, the 95% prediction intervals describe the range in which future effects of individual studies might be expected (IntHout et al., 2016).

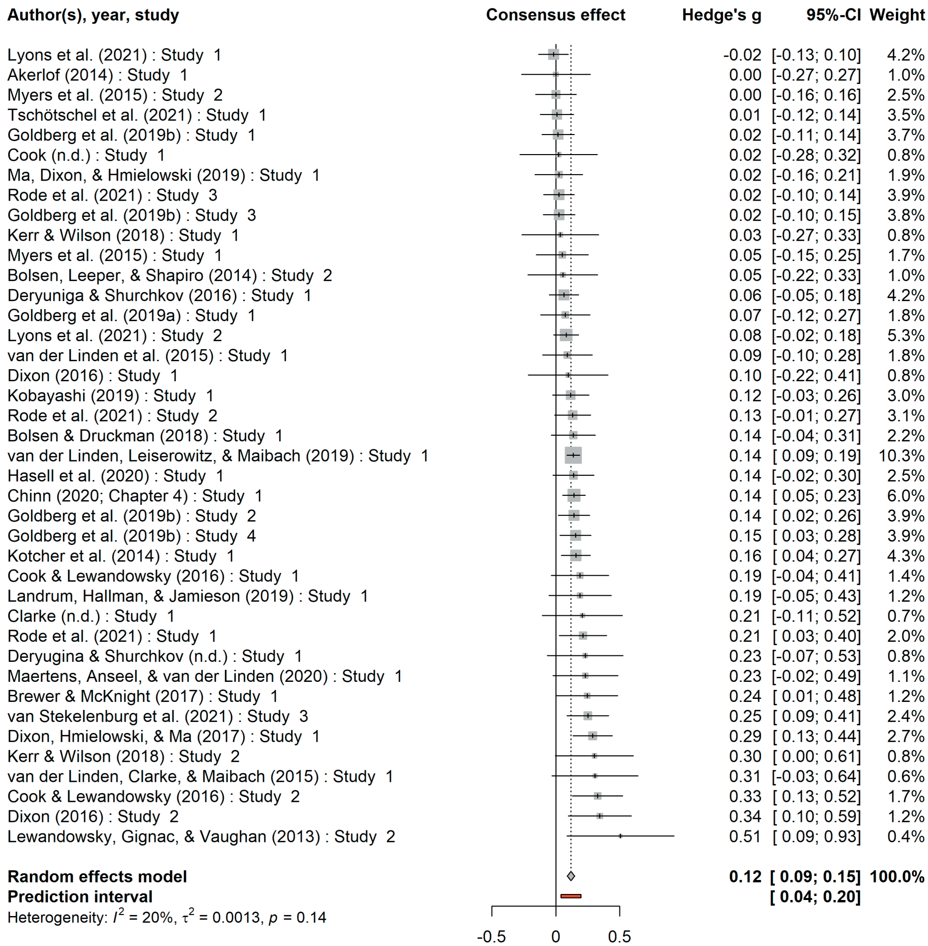
Figure 2 Forest Plot of the Effects of Scientific Consensus Communication on Perceived Scientific Consensus



Belief in Scientific Facts

The estimated average effect size of scientific consensus communication on belief in scientific facts was g = 0.12 (95% CI: 0.09 to 0.15), which differed significantly from zero $t(39)$ = 8.15, p < .001, meaning that here too a statistically significant meta-analytic effect was identified. Figure 3 shows a forest plot of the observed outcomes and the estimated average effect. There was no statistically significant heterogeneity in the effects of scientific consensus communication on belief in facts between experiments, τ^2 = 0.001, $Q(39)$ = 48.72, p < .137, I^2 = 19.9% (95% CI: 0% to 46.2%). This is reflected in a relatively narrow 95% prediction interval, which ranges from 0.04 to 0.20.

Figure 3 Forest Plot of the Effects of Scientific Consensus Communication on Belief in Scientific Facts



Topic

A second preregistered goal of this meta-analysis was to investigate the effect of consensus communication per contested science topic, which is not only of theoretical and practical value, but also functioned as a sensitivity analysis for the overall effects of scientific consensus communication. A random-effects model for between-subgroup-effects demonstrated that there were no significant subgroup differences between the three topics related to perceived scientific consensus, $Q(2) = 0.87$, $p = .649$. The effects for climate change (k = 27), $g = 0.56$, 95% CI: 0.41 to 0.72, and genetically modified food (k = 8), $g = 0.56$, 95% CI: 0.19 to 0.92, were almost identical in size. The estimated effect of scientific consensus communication regarding vaccination was smaller (k = 2), $g = 0.29$, 95% CI: -3.26 to 3.85, but this effect was based on only two experiments. See Table 3 for an overview of all results.

Table 3 Overview of the Results of the Meta-analysis

Analysis		Perceived scientific consensus					Belief in scientific facts				
		k	*g* / *b* (95% CI)	*p*	I^2 (95% CI)	95% PI	*k*	*g* / *b* (95% CI)	*p*	I^2 (95% CI)	95% PI
Main effects		37	0.55 (0.42 - 0.68)	< .001	95.2%	-0.22 - 1.32	40	0.12 (0.09 - 0.15)	< .001	19.9%	0.04 - 0.20
~ by topic	Climate change	27	0.56 (0.41 - 0.72)	< .001	95.2%	-0.22 - 1.34	30	0.12 (0.08 - 0.15)	< .001	15.1%	0.05 - 0.18
	GM food	8	0.56 (0.19 - 0.92)	.009	94.3%	-0.52 - 1.64	8	0.16 (0.08 - 0.23)	.002	1.9%	0.03 - 0.28
	Vaccination	2	0.29 (-3.26 - 3.85)	.484	89.3%	NA	2	0.10 (-1.89 - 2.09)	.629	68.4%	NA
Sensitivity analyses	Different estimator	37	0.54 (0.43 - 0.66)	< .001	95.2%	-0.15 - 1.24	40	0.12 (0.09 - 0.15)	< .001	19.9%	0.04 - 0.20
	Exclude extreme effect sizes	22	0.55 (0.47 - 0.63)	< .001	71.2%	0.23 - 0.87	NA	NA	NA	NA	NA
	Exclude influential effect sizes	34	0.46 (0.36 - 0.56)	< .001	94.2%	-0.08 - 1.01	38	0.12 (0.09 - 0.14)	< .001	4.4%	0.09 - 0.14
	Exclude potentially inflated effect sizes	32	0.44 (0.34 – 0.54)	< .001	94.5%	-0.09 – 0.97	35	0.11 (0.08 – 0.14)	< .001	12.5%	0.04 – 0.18
Reporting bias	Preregistered studies	8	0.36 (0.09 - 0.64)	.017	92.7%	-0.46 - 1.18	7	0.08 (-0.02 - 0.18)	.088	44.5%	-0.12 - 0.28
	Non-preregistered studies	29	0.60 (0.45 - 0.75)	< .001	94.6%	-0.19 - 1.39	33	0.13 (0.10 - 0.16)	< .001	4.1%	0.10 - 0.16
Moderator analyses	Conservatism	25	-0.13 (-1.71 - 1.46)	.870	91.7%	NA	28	-0.02 (-0.49 - 0.46)	.943	0.0%	NA
	Pre-existing perceptions of scientific consensus	37	-0.84 (-2.01 - 0.34)	.156	95.9%	NA	NA	NA	NA	NA	NA
	Pre-existing belief in scientific facts	NA	NA	NA	NA	NA	39	-0.16 (-0.38 - 0.06)	.151	18.7%	NA

Note. NA = not available. CI = confidence interval. PI = prediction interval. Hedge's *g* is reported for all analyses except for the moderator analyses, where instead a regression coefficient (*b*) is reported.

Moving to factual beliefs, we again found that there are no significant subgroup differences between topics, $Q(2) = 1.36$, $p = .507$, although the effect for climate change (k = 30), $g = 0.12$, 95% CI: 0.08 to 0.15 was descriptively smaller than for genetically modified food (k = 8), $g = 0.16$, 95% CI: 0.08 to 0.23. The effect for vaccination (k = 2) was descriptively even smaller, $g = 0.10$, 95% CI: -1.89 to 2.09, though again this was based on only two experiments.

Sensitivity Analysis

As preregistered, we conducted two additional sensitivity analyses, aiming to provide insight into the robustness of the scientific consensus communication effects. First, because different heterogeneity estimators in meta-analysis can produce different results (Langan et al., 2019; e.g., van der Linden & Goldberg, 2020), we compared the results obtained using the REML estimator and KHSJ CIs to those obtained using a conventional random-effects analysis (using the DerSimonian-Laird estimator without KHSJ method). This resulted in almost identical estimated effect sizes both for perceived scientific consensus, $g = 0.54$ (95% CI: 0.43 to 0.66) and factual beliefs, $g = 0.12$ (95% CI: 0.09 to 0.15).

Second, we searched for extreme and influential effect sizes. Regarding perceived scientific consensus, a large number of extreme cases (k = 15) was identified as completely falling outside the 95% CI of the pooled effect (i.e., the 95% CI of an effect did not overlap with the 95% CI of the pooled effect). Rerunning the main analysis without these 15 extreme cases resulted in an almost identical average estimated effect size, $g = 0.55$ (95% CI: 0.47 to 0.63), although it should be noted that the I^2 was lower (71.2%) and the 95% prediction intervals no longer included negative effects (0.23 to 0.87). Using a stricter criterion for extreme cases, effect sizes falling outside the 95% prediction interval, only three effect sizes were identified as extreme (Cook & Lewandowsky (2016): Study 1 and Study 2, Kerr & Wilson (2018): Study 2). These three experiments were also identified as influential cases by investigating the standardized residuals and Cook's distance, following general advice from Viechtbauer & Cheung (2010). Excluding these effect sizes substantially reduced the average estimated effect size for perceived scientific consensus, $g = 0.46$ (95% CI: 0.36 to 0.56), but heterogeneity remained high ($I^2 = 94.2\%$, 95% prediction interval -0.08 to 1.01). Additionally, these three effect sizes, as well as two others (Kerr & Wilson (2018): Study 1, Lewandowsky et al. (2013): Study 2), were extracted from experiments in which a posttreatment check directly related to the experimental manipulation was used to exclude participants. This procedure may have affected the results of these experiments (Montgomery et al., 2018), potentially inflating effects. For this reason, we conducted an additional, unplanned sensitivity analysis to investigate the effect of these five cases on the meta-analytic estimate of the effect of scientific consensus communication on perceived scientific consensus. The results yielded an again slightly smaller estimate, g = 0.44 (95% CI: 0.34 to 0.54) while heterogeneity remained high ($I^2 = 94.5\%$, 95% prediction interval -0.09 to 0.97).

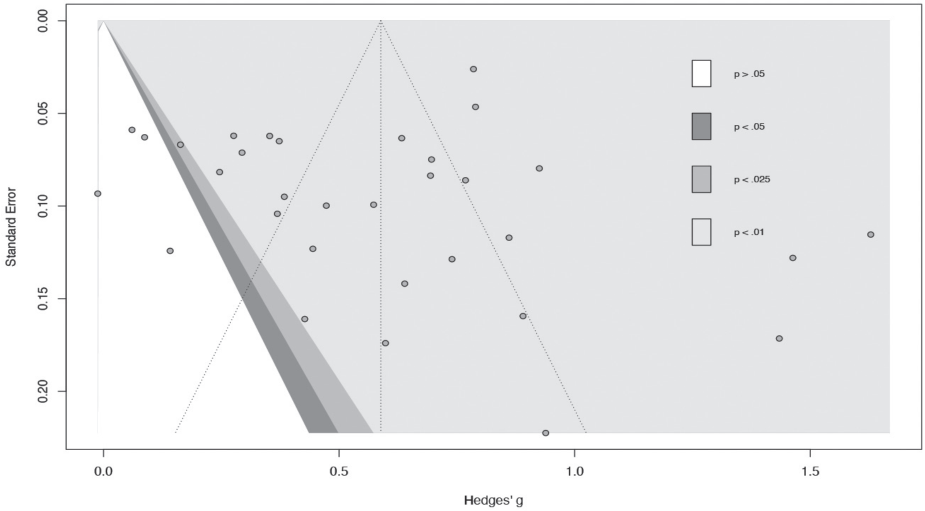
Moving to factual beliefs, no extreme effect sizes were identified using the 95% CIs or 95% prediction interval. Two influential effect sizes could be identified based on the standardized residuals and Cook's distance (Dixon, Hmielowski, & Ma (2017): Study 1 and Lyons et al. (2021): Study 1), but removal of these two effect sizes had almost no effect on the results of the main analysis, g = 0.12 (95% CI: 0.09 to 0.14). Finally, we reran the analysis without the five cases that used a procedure that potentially inflated effects of a consensus message on perceived scientific consensus and thus potentially also indirectly inflating effects on belief in scientific facts. The results yielded a slightly smaller main effect of consensus messaging on belief in scientific facts, g = 0.11 (95% CI: 0.08, 0.14).

Additionally, and not preregistered, we created Graphic Display of Heterogeneity (GOSH) plots (Olkin et al., 2012) to explore patterns of heterogeneity in the data and extend our search for extreme and influential cases. We found no obvious patterns that could explain the high heterogeneity as indicated by I^2 for perceived scientific consensus. In line with the results from the investigation of extreme and influential cases, there was some indication that the average estimated effect size for perceived scientific consensus might be inflated somewhat. We did not find that the main results related to factual beliefs changed substantially with different combinations of experiments (see online Supplemental Material).

Reporting Bias

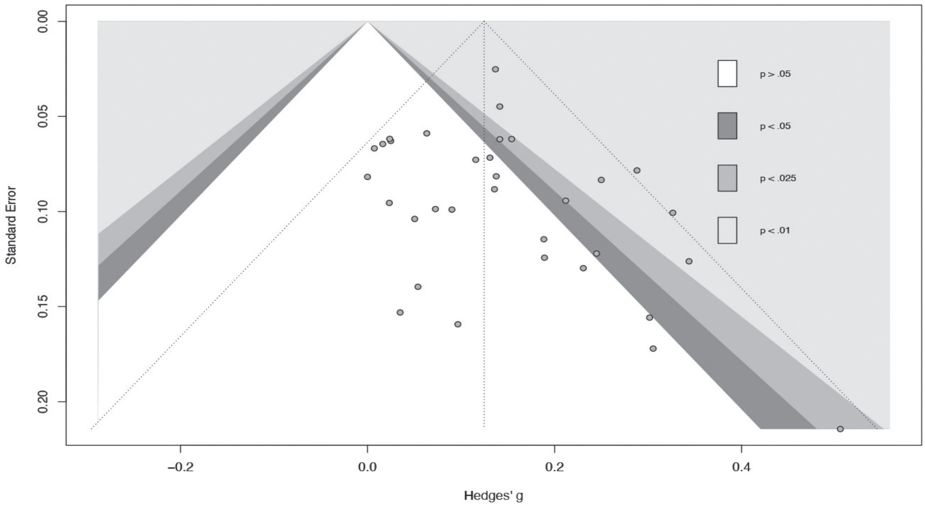
As preregistered, reporting bias was investigated in two ways. First, we investigated evidence of a small-study bias, which is an indirect indicator of reporting bias, in the subset of experiments from articles that were published or accepted for publication at the time of the writing (k = 32 for perceived scientific consensus, k = 33 for factual beliefs). Visual inspection of the contour-enhanced funnel plot of the effects of scientific consensus communication on perceived scientific consensus revealed no asymmetry (see Figure 4). This was confirmed by Egger's test for asymmetry, which was non-significant, intercept = -0.47, (95% CI: -3.83 to 2.89), t = -0.27, p = .786. Visual inspection of the contour-enhanced funnel plot of the effects of scientific consensus communication on belief in scientific facts revealed some asymmetry (see Figure 5). Egger's test, however, was again non-significant, intercept = 0.55, (95% CI: -0.28 to 1.37), t = 1.30, p = .202.

Figure 4 Contour-enhanced Funnel Plot of the Effects on Perceived Scientific Consensus



Note. The funnel plot shows observed effect sizes versus their standard errors. The dotted lines indicate the pooled random effects estimate.

Figure 5 Contour-enhanced Funnel Plot of the Effects on Belief in Scientific Facts



Note. The funnel plot shows observed effect sizes versus their standard errors. The dotted lines indicate the pooled random effects estimate.

Second, using the same subset of articles that were published or accepted for publication, the three-parameter selection model (McShane et al., 2016) was implemented to assess the effects of publication bias on our meta-analytic estimates. Selection models aim to model the effect of publication bias on the selection of experiments included in a meta-analysis. They are based on the assumption that the size, direction, and *p* value of study results and the size of studies influences the probability of their publication (Page, Higgins, et al., 2021). Neither of the tests provided reason to believe that the meta-analysis was biased by a lower selection probability of non-significant results (perceived scientific consensus: $\chi^2(1) = 0.92$, $p = .337$, factual beliefs: $\chi^2(1) = 0.01$, $p = .935$).

In addition to these two preregistered investigations of reporting bias, we explored (not preregistered) whether there were differences in effect sizes for preregistered experiments vs non-preregistered experiments, including both published and (yet) unpublished experiments. Effect sizes in psychological research have been found to differ substantially between preregistered and non-preregistered work (Schäfer & Schwarz, 2019), most likely due to the effects in non-preregistered experiments being over-estimations. In the current meta-analysis, however, there were no significant subgroup differences between preregistered and non-preregistered experiments related to perceived scientific consensus, $Q(1) = 2.95$, $p = .086$, and factual beliefs, $Q(1) = 1.45$, $p = .229$. It should be noted, however, that this subgroup analysis was likely underpowered due to the low number of preregistered works and the high heterogeneity in the case of effects on perceived scientific consensus. This low power is reflected in the wide confidence intervals around the estimated subgroup effects. Notably though, for both perceived scientific consensus and factual beliefs the estimated average effect was descriptively smaller for preregistered experiments ($k_{consensus} = 8$, $g_{consensus} = 0.36$, 95% CI: 0.09 to 0.64; $k_{belief} = 7$, $g_{belief} = 0.08$, 95% CI: -0.02 to 0.18) than for non-preregistered experiments ($k_{consensus} = 29$, $g_{consensus} = 0.60$, 95% CI: 0.45 to 0.75; $k_{belief} = 33$, $g_{belief} = 0.13$, 95% CI: 0.10 to 0.16).

Additional Moderators

Analyses of the following moderators was not preregistered. As standard meta-regression methods can suffer from inflated false-positive rates, we conducted permutation tests to control for spurious findings (Higgins & Thompson, 2004). The general results of these permutation tests did not differ from the results of standard meta-regression described below (see online Supplemental Material for more detail).

Conservatism

All samples of experiments conducted in the US that included a measure of political ideology (k = 30) were coded on how conservative (versus liberal) the samples were. To make best of the available information from the original experiments we calculated a continuous score of sample conservatism, for which each sample received a score from 0 to 1, indicating the ratio of participants that identified themselves in any way as conservative. Overall, the samples skewed liberal (*M* = 0.43, SD = 0.07). The measure of conservatism was then included in meta-regression of the original effects on perceived scientific consensus (k = 25) and factual beliefs (k = 28).

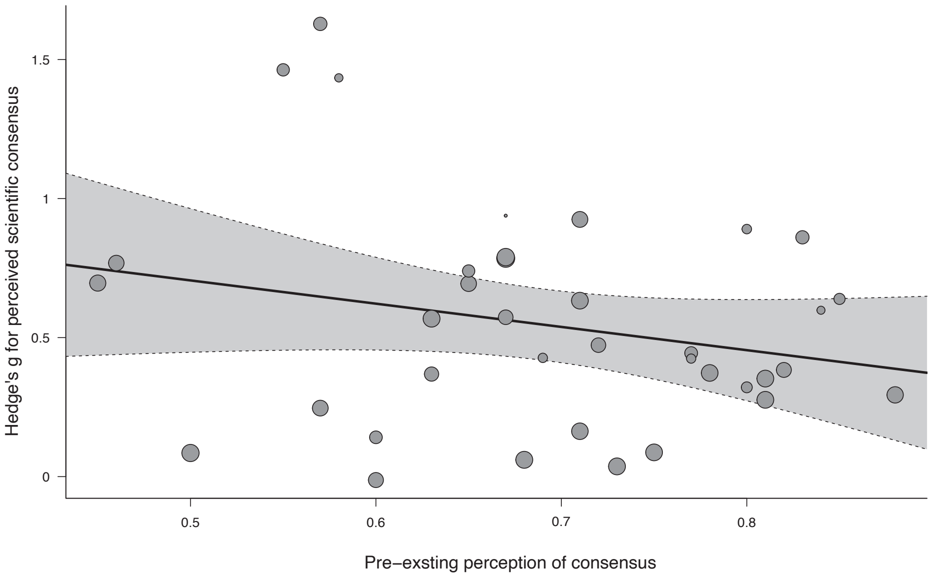
For both perceived scientific consensus and factual beliefs, the moderator tests were non-significant, $b = -0.13$, $t(23) = -0.17$, $p = .870$ and $b = -0.02$, $t(26) = -0.07$, $p = .943$, respectively. Additionally, we explored whether conservatism might interact with topic (in effect forming a three-way interaction among scientific consensus communication, conservatism, and topic), comparing climate change to GM food. Here too, the interaction effects were non-significant, $b = -1.68$, $t(20) = -0.53$, $p = .600$ and $b = -0.95$, $t(23) = -0.90$, $p = .378$, respectively.

Pre-existing Perceptions of Scientific Consensus

All samples were coded on their pre-existing perceptions of scientific consensus. Where possible, we used pre-manipulation measures of perceived scientific consensus for the consensus condition(s), which is the most relevant indicator of how much room for improvement there was in the treatment conditions. If no pre-manipulation measure was available, we used the post-manipulation score of perceived scientific consensus of the control condition as a proxy. These scores were all recoded to a 0 to 1 scale, with higher scores indicating a higher estimate of scientific consensus in line with the scientific facts. Overall pre-existing perceptions were quite high, with a mean of 0.69 (SD = 0.11), which in most experiments roughly referred to an estimate of 69% of scientists agreeing over the scientific facts.

Meta-regression indicated no significant moderating effect of pre-existing perceptions of consensus, $b = -0.84$, $t(35) = -1.44$, $p = .159$. The trend indicated that there might be a negative moderating effect of pre-existing perceptions of consensus, such that samples with low consensus perceptions yielded larger effects of consensus messaging, see Figure 6. It should be noted, however, that this trend largely disappears if the five experiments with potentially inflated effects of consensus messaging on perceived scientific consensus (see Sensitivity Analysis) are excluded, $b = -0.09$. Here too, a potential interaction among pre-existing perceptions of consensus and topic was explored, including only the climate change and GM food experiments. Again, no significant interaction effect was found, $b = 1.52$, $t(31) = 0.80$, $p = .428$.

Figure 6 Meta-regression Scatter Plot of Pre-existing Perception of Consensus and the Effect of Scientific Consensus Communication on Perceived Scientific Consensus

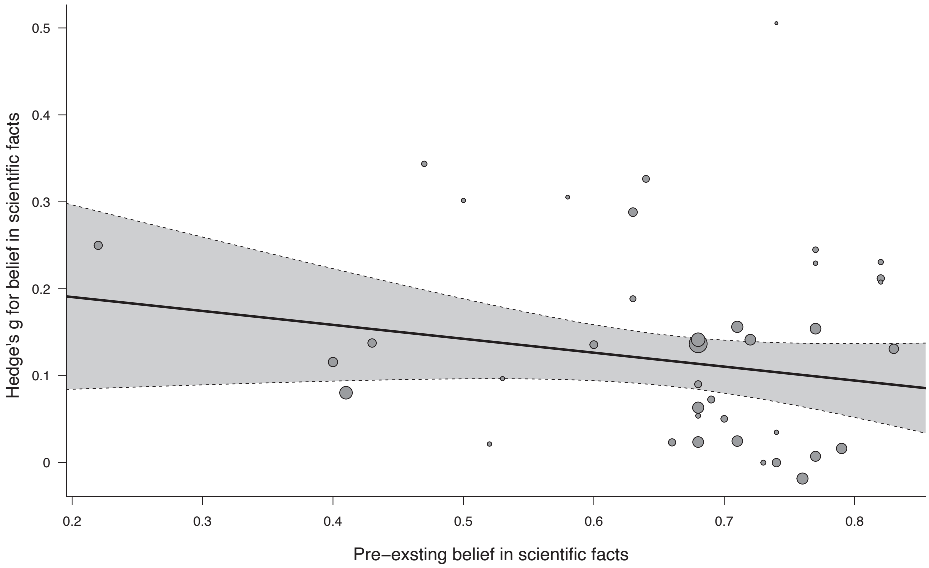


Note. Point sizes reflect the weight that the experiment received in the analysis, with bigger points indicating more weight. The gray area indicates the 95% CI.

Pre-existing Belief in Scientific Facts

A similar procedure was employed to code samples on their pre-existing belief in scientific facts, also coded on a scale of 0 to 1 with higher scores indicating beliefs more in line with the scientific facts. Overall pre-existing beliefs were quite accurate, with a mean of 0.65. Meta-regression indicated no significant moderating effect of pre-existing beliefs, $b = -0.17$, $t(34) = 1.51$, $p = .141$, but provided tentative descriptive evidence for a negative association, see Figure 7. Here too, a potential interaction among pre-existing perceptions of consensus and topic was explored, including only the climate change and GM food experiments. Again, no significant interaction effect was found, $b = -0.13$, $t(30) = -0.24$, $p = .810$.

Figure 7 Meta-regression Scatter Plot of Pre-existing Belief in Scientific Facts and the Effect of Scientific Consensus Communication on Belief in Scientific Facts



Note. Point sizes reflect the weight that the experiment received in the analysis, with bigger points indicating more weight. The gray area indicates the 95% CI.

Discussion

This meta-analysis assessed the effects of communicating the existence of scientific consensus on perceptions of scientific consensus and belief in scientific facts regarding contested science topics. The results of 43 experiments demonstrate that, across topics, single exposure to scientific consensus messaging has a significant positive effect on perceived scientific consensus (g = 0.55). This effect is slightly smaller than a recent estimation of the median effect size in (non-preregistered) social psychology studies (g = ~0.63 ; Schäfer & Schwarz, 2019) but larger than a recent estimation of the median effect size in communication science (g = ~0.37; Rains et al., 2018). The estimated average effect of scientific consensus communication on factual beliefs was smaller (g = 0.12) than for perceived scientific consensus, but still significant.

These findings demonstrate that scientific consensus communication is an effective approach to help people find out the facts about contested science topics. But while the effect of consensus communication on perceived scientific consensus is large enough to be practically relevant after single exposure, the effect on factual beliefs is smaller and might only be practically relevant if it can be magnified (e.g., with repeated exposure; Anvari et al., n.d.; Funder & Ozer, 2019). Moreover, most experiments included in the current meta-analysis consist of online experiments where single, short messages are presented in a very controlled setting. Future research would do well to test if these effects persist in less controlled environments (see also van der Linden, 2021), among publics who might be less inclined to sign up to participate in scientific research, and if larger effects can be achieved through repeated exposure or more elaborate messages. Such experiments in the more noisy, real-life media landscape would also be of great value for science communication practice.

There is some concern among science communication scholars that accurate information, such as scientific consensus messages, might not be effective in informing the general public or might even "backfire", leading to contrary belief updating by some (e.g., Hart & Nisbet, 2012; Kahan et al., 2011). Communicating the facts would thus result in large scale polarization. In contrast, the findings of this meta-analysis are in line with other recent work (e.g., Nyhan, 2021; Swire-Thompson et al., 2020; van Stekelenburg et al., 2020; Wood & Porter, 2019), showing that communicating accurate (corrective) information, in this case information regarding agreement among scientists, is a viable strategy to inform the public. Although it is unlikely that the effects of scientific consensus messaging are exactly the same for all individuals, this meta-analysis indicates that the likelihood of such messages resulting in null effects or backfiring overall are slim.

Concerning potential differing effects between parts of the public, sample conservatism did not significantly moderate the effect of scientific consensus communication, nor did it interact with topic to do so. The moderating effects of the sample's pre-existing perceived scientific consensus and factual beliefs were also non-significant. If anything, plots indicated scientific consensus communication might be more effective for skeptics than for people whose personal beliefs are already more or less in line with scientific evidence. Of course, there is also more room for these people to change their beliefs. Thus, while noting caution in interpreting the results of potentially underpowered meta-regression analyses (see limitations, below), we find no evidence of scientific consensus messaging being ineffective or backfiring among specific publics. Difficulty in determining when scientific consensus communication is effective for whom, combined with the relatively small immediate effect on belief in scientific facts, is likely what has kept the discussion about its effectiveness as a science communication strategy going.

The main results appear rather robust. First, regarding the three different topics, we found that the effects of scientific consensus communication were very similar for climate change and genetically modified food. We identified only two experiments that investigated scientific consensus communication in the context of vaccination (although more research might be upcoming due to the COVID-19 pandemic, e.g., Kerr & van der Linden, 2021), which prevents us from drawing conclusions regarding this topic specifically. Second, regarding extreme and influential cases, the main results related to perceived scientific consensus might be inflated somewhat (removal of extreme, influential, or potentially inflated effect sizes yielded *g*'s of 0.44 and 0.46), while the effect related to belief in scientific facts is largely robust in this context. Finally, we found no evidence of publication bias. However, it should be noted that the estimated average effects for preregistered studies were descriptively smaller than for non-preregistered studies.

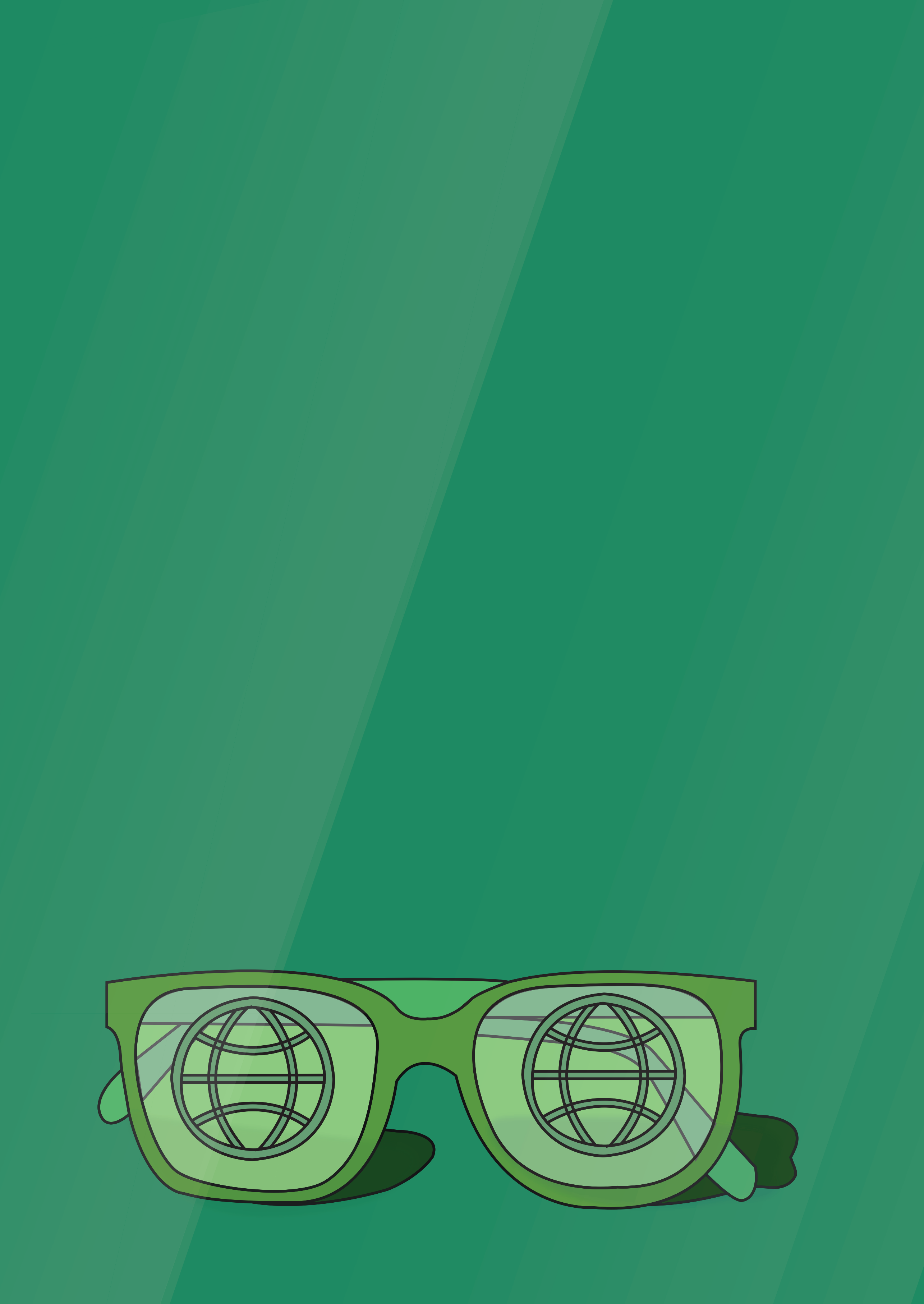
The main results of this meta-analysis are in line with recent meta-analytic work focusing on climate change communication (Rode, Dent, et al., 2021). This research focused on a variety of interventions and outcomes, but included 18 articles testing scientific consensus and showed that scientific consensus communication has a significant, positive effect on climate change attitudes (g = 0.09, 95% CI [0.05, 0.13]). Interestingly, this and other meta-analytic work (Hornsey et al., 2016) suggest that changing beliefs is easier than changing support for policy or willingness to act. One potential explanation is that it takes some time for changes in factual beliefs to affect these further downstream variables that are more closely related to real-life consequences. Future (meta-analytic) work might focus on long-term effects, investigating if and how communicating scientific consensus might influence not only perceptions of consensus and beliefs, but also variables like support for policy or behavior in the long run.

There are three limitations to this meta-analysis that should be taken into account when interpreting the results. The first one pertains to the moderator analyses. Because of the nature of the aggregated data that forms the input of the meta-analysis, there was limited variation in the samples' levels of conservatism and pre-existing perceptions of scientific consensus and factual beliefs (an 'aggregation bias'; Deeks et al., 2021). Additionally, political conservatism was only investigated as a moderator in US samples, to ensure that conservatism measured more or less the same construct across experiments. These factors may have decreased power to detect a true moderating effect, resulting in wide confidence intervals around the meta-regression estimates. The consistently high heterogeneity in effects of consensus messaging on perceived scientific consensus does indicate that substantial variation in effects on this outcome (but not belief in scientific facts) between experiments is left unexplained.

A second limitation is that the current meta-analysis only investigated effects of scientific consensus messaging on perceptions of scientific consensus and factual beliefs related to the specific information about which scientific consensus was communicated. When a consensus message stated that "90% of medical scientists agree that vaccines are safe" we included effect sizes related to personal belief about the safety of vaccines in the meta-analysis, but not effects for potentially related beliefs about issues such as the false link between vaccines and autism. Therefore, the average estimated effects should be most applicable to situations where the scientific consensus message is highly related to the factual belief one aims to affect. Future (meta-analytic) work might investigate if and how the effects of scientific consensus messages influence beliefs that were not directly addressed.

A third limitation is related to the indirect effect of scientific consensus communication on belief in scientific facts through perceived scientific consensus, as hypothesized in the gateway belief model (van der Linden, Leiserowitz, et al., 2015). Statistical experts have substantial reservations with mediation analysis in the way that it is often conducted to test for indirect effects in social science research (see e.g., Bullock et al., 2010; Fiedler et al., 2011; Montgomery et al., 2018). Many of these reservations also pertain to the research synthesized here. This prohibits us from conducting statistical procedures aimed at meta-analytically testing the hypothesized indirect effect. Nonetheless, the results of the meta-analysis can be argued to provide some tentative support for the hypothesis that the effect of consensus messaging on personal beliefs is a function of a change in perceptions of consensus: the effect sizes related to perceived scientific consensus and belief in scientific facts in the included research correlate substantially ($r = 0.56$, $p = .001$). This correlation, however, is only a very tentative indication of a potential indirect effect. Future research is needed to specifically address the causal chain hypothesized in the gateway belief model.

To conclude, communicating a high degree of scientific consensus regarding contested science topics can be a useful tool in science communicators' toolkit. Such messaging increases perceptions of scientific consensus as well as the accuracy of beliefs related to these science topics. Notably, an important benefit of consensus messaging is that it comes at a low cost and consists simply of informing people. It does not mislead or covertly change behavior; it empowers the public by providing valuable information that can support informed decision making. It is up to the recipient of the message to decide whether this information is of value to their personal beliefs. The current work suggests that many people put at least some value in scientific consensus and are willing to update their beliefs if they are not in line with such consensus.



Chapter 4

Boosting Understanding and Identification of Scientific Consensus Can Help to Correct False Beliefs

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Abstract

Some people hold beliefs that are opposed to overwhelming scientific evidence. Such misperceptions can be harmful to both personal and societal well-being. Communicating scientific consensus has been found effective in eliciting scientifically accurate beliefs, but it is unclear whether it is also effective in correcting false beliefs. Here we show that a boosting strategy that empowers people to understand and identify scientific consensus can help to correct misperceptions. In three experiments with over 1,500 US adults holding false beliefs, participants first learned the value of scientific consensus and how to identify it. Subsequently, they were exposed to a news article with information about a scientific consensus opposing their belief. We found strong evidence that in the domain of genetically engineered food this two-step communication strategy is more successful in correcting misperceptions than merely communicating scientific consensus. The data suggest the current approach may not work for misperceptions about climate change.

Keywords: misperceptions, belief change, boosting, scientific consensus, science communication, climate change, genetically engineered food, open data, preregistered

Boosting Understanding and Identification of Scientific Consensus Can Help to Correct False Beliefs

Some people hold beliefs that are opposed to overwhelming scientific evidence. These misperceptions, defined as factual beliefs that are false or contradict the best available evidence in the public domain (Flynn et al., 2017), can be harmful to one's health and even hamper society's ability to address major challenges. One of the biggest challenges of our time is climate change, for which public policy and action depend on the accurate belief that climate change is caused by human action (Krosnick et al., 2006; van der Linden, Leiserowitz, et al., 2015). Similarly, accurate beliefs about vaccination influence the decision to vaccinate (Joslyn & Sylvester, 2019), which is our most promising approach to eradicate diseases such as polio, diphtheria, and measles. In the domain of food technology, substantial opposition to genetic engineering of food (Scott et al., 2016, 2018) means that we stand to lose support for one of the most promising technologies to reduce undernourishment, from which an estimated 821 million people suffer globally (United Nations, n.d.). The goal of the current research is to test a communication strategy aimed at correcting misperceptions about important societal issues.

Communicating scientific information can be problematic because people typically take their own goals and needs, knowledge and skills, and values and beliefs into account when evaluating new information (National Academy of Sciences, 2017). This makes effective science communication more difficult than the act of simply providing information. Instead of communicating complex knowledge, research has found that communicating scientific consensus (i.e., a high degree of agreement among scientists) is effective in eliciting accurate beliefs (Cook, 2016). The gateway to these personal factual beliefs is the individual's perception of the agreement among scientists, their perceived consensus (Lewandowsky, Gignac, & Vaughan, 2013). This approach is thought to be effective because communicating scientific consensus does not rely on elaborate processing of complex, scientific information. Rather, it plays into heuristics such as trust in experts and the idea that consensus implies correctness (van der Linden, Leiserowitz, et al., 2019).

The heuristic to trust in expert consensus is not only an ecologically rational strategy, it also provides science communicators with a route to personal beliefs. This route through communication of scientific consensus is captured in the gateway belief model (van der Linden, Leiserowitz, et al., 2015, 2019) and is supported by extensive research. This research demonstrates that communicating the existence of a scientific consensus leads to an increase in people's perceived scientific consensus, which in turn strengthens accurate personal beliefs, even on controversial issues like climate change, vaccines, and genetically engineered food (e.g., Cook, 2016; Goldberg et al., 2019; Kerr & Wilson, 2018; Lewandowsky et al., 2013; van der Linden et al., 2019; van der Linden, Clarke, et al., 2015).

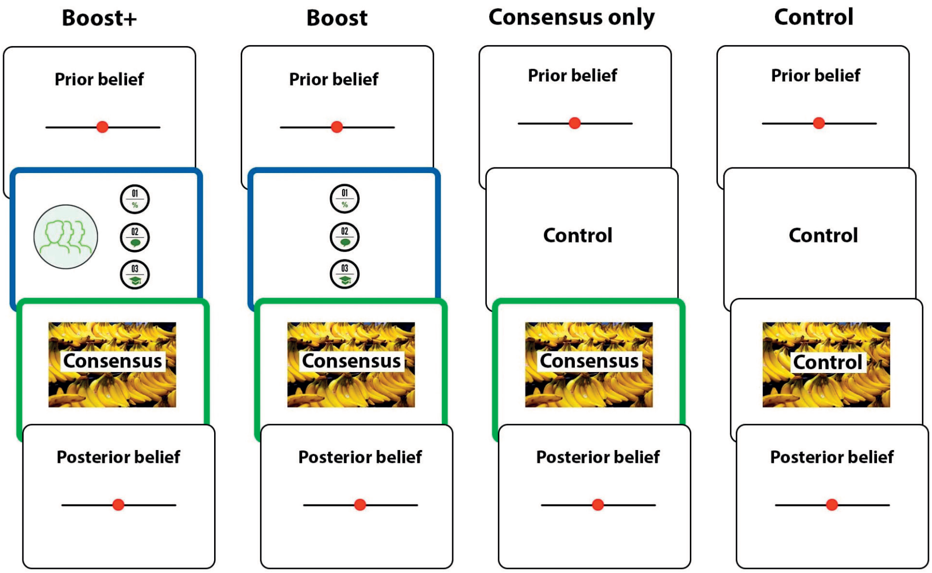
However, an important unanswered question is whether communicating scientific consensus is also effective in correcting beliefs of people who hold a misperception. Misperceptions are notoriously hard to correct, especially in the case of politicized science issues like climate change (Flynn et al., 2017). The question of how to correct misperceptions is important for two reasons. First, those who hold false beliefs may display behaviors that are detrimental to themselves or others. Second, people holding misperceptions might not trust experts advocating positions incongruent with their preferences (Kahan et al., 2011), or might downplay the reliability of a consensus cue that is in contrast to their interests (Giner-Sorolila & Chaiken, 1997). Moreover, even when the scientific consensus is accepted by individuals with a conflicting worldview (van der Linden et al., 2018; van der Linden, Leiserowitz, et al., 2019), this may not necessarily prompt them to update their personal beliefs to be in line with the consensus (Bolsen & Druckman, 2018; Dixon, 2016; Pasek, 2018). This means that communicating scientific consensus may not be persuasive among those who need persuasion most. At the same time, consensus communication is one of the most promising strategies aimed at correcting false beliefs. Thus, the challenge is to make consensus communication 'work' among people holding misperceptions in the face of overwhelming scientific evidence.

To address this challenge, we developed and tested a strategy that teaches people the value of scientific consensus and how to identify it when evaluating the veracity of a claim. The current strategy can be considered a 'boosting' approach to behavior change, which consists of a noncoercive intervention strategy that aims to increase people's competence to make their own choices. This competence can be fostered in a number of ways, such as through changes in skills or knowledge, but to classify as a boost an intervention needs to be transparent and promote agency (Hertwig & Grüne-Yanoff, 2017; Lorenz-Spreen et al., 2020). An example of boosting is when individuals are 'inoculated' against the persuasive effect of misleading information by warning them of impending exposure to such misleading information and explaining to them how the misleading technique works (e.g., the use of fake experts; Cook et al., 2017). Such inoculation may foster the skill to identify manipulative methods used to misinform and thus promote agency by making people more resistant to manipulation (Lorenz-Spreen et al., 2020). In contrast to misinformation-focused strategies such as inoculation, the goal of the present strategy is to strengthen the corrective effect of accurate information.

In the current work, we apply the boosting approach to empower individuals holding misperceptions to understand the value of and to identify scientific consensus. Thus, in contrast to providing more information, boosting consensus reasoning is intended to empower individuals to make the best use of already available information. When the boost is successful, consensus information does not only play into heuristics, but is also fully understood as a source of valuable information and is easily identified. This empowerment, combined with exposure to information about a scientific consensus embedded in a naturalistic environment, might also yield less resistance than more direct means of persuasion, because direct means of persuasion may be perceived as deceiving or as a threat to freedom (Fransen et al., 2015)S. Therefore, we expect a two-step communication strategy, consisting of (1) boosting consensus reasoning and (2) consensus information, to be more effective at helping to correct false beliefs than only communicating consensus itself.

This approach of boosting consensus reasoning was examined in three preregistered experiments. The general set-up of all three experiments in the current research was similar (see Figure 1 for an overview of all conditions employed across the experiments). The most substantial difference between experiments is the added control condition in Experiment 3 (the condition on the far right in Figure 1), which allowed us to investigate whether boosting consensus reasoning strengthened an already persuasive consensus statement, or whether the consensus statement alone was ineffective in correcting the misperception.

Figure 1 Overview of Conditions Across the Experiments



Note. In all conditions, participants' belief was measured at the start and at the end of the experiment, allowing us to investigate changes in belief. Boost+ condition (all experiments): Participants read an infographic explaining the process through which a scientific consensus is reached and why a scientific consensus is a useful piece of information when deciding whether or not something is true. The infographic also set out three steps through which one can use information about a scientific consensus to evaluate a claim (i.e., look for a statement indicating consensus, check the source of the consensus statement, and check the expertise of the consensus). Subsequently, participants were provided with the opportunity to apply their new skill by reading a news article containing a short paragraph with a statement about the scientific consensus regarding the topic of misperception. Boost condition (Experiments 1 and 2): Similar to the boost+ condition, but a shorter version of the same infographic only set out the three steps. Consensus-only (all experiments): Participants' consensus reasoning was not boosted. Instead, they read an infographic telling them that we were interested in their strategy for evaluating claims. Subsequently, they read the news article described above containing the consensus statement. Control condition (Experiment 3): Participants read the same infographic as in the consensus-only condition. However, the news article they subsequently read did not contain a statement about the scientific consensus. The boost conditions are indicated in blue, the conditions with a consensus statement in green.

Experiment 1 – Climate Change

In Experiment 1 we addressed the misperception that climate change is not caused by human action. We were interested in climate change because this is one of the most challenging topics in science communication, where the belief that climate change is human-caused functions as an important predictor of climate change risk perception (Lee et al., 2015).

Method

All participants in Experiment 1 were screened and selected in such a way that at the start of the experiment they held the belief that climate change is not primarily caused by human action. Participants' belief in human-caused climate change was measured at the start and end of the experiment (prior and posterior belief, respectively). We hypothesized that boosting consensus reasoning would lead to higher posterior belief in human-caused climate change than the consensus-only condition. Second, we expected the longer boost, the boost+, to have a greater corrective effect than the short boost, because the boost+ included an explanation of the value of scientific consensus. By testing effects on participants' posterior belief, statistically correcting for their prior belief, we investigated their change in belief.

The hypotheses, sampling procedure, main analyses, and exclusion criteria for all experiments were preregistered on OSF: https://osf.io/7aqjp/ (Experiment 1), https://osf.io/kd7hb/ (Experiment 2), and https://osf.io/4w9tq/ (Experiment 3). Material, data, and analysis scripts for all three experiments are also available on OSF (https://osf.io/hua8v/). All three experiments were part of a research project that was reviewed and approved by the Ethics Committee Social Science at Radboud University (Reference No. ECSW-2018-056).

Participants

Participants (US nationals) were recruited using online research platform Prolific (www.prolific.co), following a Bayesian sequential sampling procedure with optional stopping (Schönbrodt et al., 2017). During the sequential sampling procedure, we checked the Bayes factor (BF) at predetermined intervals to evaluate the evidence in the data for or against the hypotheses. We planned to continue data collection until there was moderate evidence (Schönbrodt et al., 2017; $1/6 > BF_{10} > 6$) in favor of or against our hypotheses or until a maximum *N* (450) was reached. We started checking the BFs at 50% of the maximum *N*: 225 participants. This was enough to detect a medium effect size ($\eta_p^2 = .066$) with 0.90 power and alpha = .05 for hypothesis 2, with the smaller subsample (Faul et al., 2009). We had planned to continue to check the BFs after every set of 45 (10% of maximum *N*) new participants. If at any time both BFs had reached the required level of evidence for or against the hypotheses, data collection would have been stopped. However, screening participants incurred substantially higher costs than expected, due to the fact that there were less climate skeptics in the participant pool than we expected. Therefore, in contrast to the preregistration, data collection was halted at the first check (final $N = 222$; 49.10% female, $M_{Age} = 44.17$, $SD_{Age} = 14.24$; see Table 1 for sample sizes per condition; see online Supplemental Material for full sampling procedure).

Table 1 Total Sample Size, Exclusions, and Final Sample Size per Experiment per Condition

Experiment	Sample	Condition				
		Boost+	Boost	Consensus- only	Control	**Total**
Experiment 1	Total sample	87	92	92	-	**271**
	Excluded	15	16	18	-	**49**
	Final sample	72	76	74	-	**222**
Experiment 2	Total sample	163	161	165	-	**489**
	Excluded	16	12	19	-	**47**
	Final sample	147	149	146	-	**442**
Experiment 3	Total sample	318	-	327	327	**972**
	Excluded	43	-	40	35	**118**
	Final sample	275	-	287	292	**854**

Note. Exclusions mainly consist of preregistered exclusion criteria that participants should hold a misperception at the start of the experiment, failing an instructed-response item, and reporting a different nationality (i.e., non-US) than we screened for. However, a small number of participants were excluded post hoc (see online Supplemental Material for more detail).

Materials and procedure

First, prior belief in human-caused climate change and prior perceived scientific consensus were measured. Subsequently, participants were randomly assigned to one of three conditions. In Experiment 1, participants were assigned to the boost+, boost, or consensus-only condition.

In all conditions, we presented participants with an infographic entitled 'How to figure out whether a claim is true'. In the boost+ condition, the infographic (containing a total of 511 words) first explained how a scientific consensus develops and why it is a useful piece of information in evaluating claims. Specifically, it described the process as beginning with a question, upon which evidence is gathered, followed by the development of a consensus, which ultimately can be used to evaluate a claim. This first part of the infographic concluded with the statement that consensus among scientists reflects consensus in the evidence. The second part of the infographic taught participants "Three steps to evaluate a claim". The three steps were (1) looking for a statement indicating consensus, (2) checking the source making the consensus statement, and (3) evaluating the expertise of the consensus. This second part of the infographic concluded with the statement that a claim that satisfies the conditions mentioned in the steps is very likely to be true.

The infographic in the shorter 'boost' condition (171 words) only consisted of the second part, setting out the three steps. In the consensus-only condition, we told participants that we were interested in their personal strategy for evaluating claims (63 words; see Appendix C for all infographics).

The consensus reasoning manipulation was piloted with US citizens on Prolific, demonstrating that the boosts were successful in eliciting consensus reasoning (*N* = 45; see Pilot Study on OSF).

After reading the infographic, all groups evaluated three practice statements that were unrelated to the actual topic of misperception that we were interested in (i.e., "According to Andreas Spigletti, more than 4 out of 5 medical doctors agree that pneumonia is caused by being exposed to low temperatures", "According to Lisa Williams from the National Academy of Sciences, 9 out of 10 psychologists agree that Greenland is about the same size as Africa", "According to dr. Kendall Smith from Leipzig University, 95% of physicists agree that electrons are smaller than atoms"). In both boost conditions, participants were asked whether, based on the three steps they just read about, the statement allowed them to judge whether the claim was true or not. Participants in the consensus-only condition evaluated the same three practice statements, but were asked whether based on their strategy of claim evaluation they could judge whether the claim was true or not. Participants in the boost conditions received feedback on whether their answer (yes or no) was correct, thereby reiterating the three steps of evaluating a claim using consensus reasoning (e.g., "Incorrect. We cannot evaluate this claim, because Step 2 cannot be completed. We do not know if the source making the statement (Andreas Spigletti) is a scientist from a university or another scientific organization. Therefore, we cannot judge whether the claim is true"). This feedback was aimed at practicing the newly acquired consensus reasoning skill. Participants in the consensus-only condition received no feedback.

Having completed the practice rounds, we presented participants with a news article about a sharp rise in Arctic temperatures. The article (322 words) included a statement on the scientific consensus regarding human-caused climate change and was adapted from an article in the Guardian (The Guardian, 2019). The consensus statement in the news article was based on research on the scientific consensus about human-caused climate change (Cook et al., 2016), presenting the conclusion: *In 2016 already, a study showed that there is a scientific consensus on human-caused global warming. Dr. John Cook from George Mason University: "The expert consensus is somewhere between 90% and 100% that agree humans are responsible for climate change, with most of the studies finding 97% consensus among publishing climate scientists".* We incorporated the scientific consensus statement in a news article to address one prominent critique of consensus messaging in the domain of climate change. Critics argue that much of the research is conducted in an artificial context, with consensus messages lacking the complexity of real-world information (Kahan, 2015; Pearce et al., 2015). By incorporating the consensus statement in a news article, participants could apply the consensus reasoning skill in a more externally valid setting than if they had received a standalone consensus message.

After reading the news article, participants' belief and perceived scientific consensus were measured again (posterior belief and posterior perceived consensus, respectively). We explained to participants that this second measure was not a test, but that we were interested in their belief. The remaining variables were measured.

Measures

Belief in human-caused climate change was measured by asking participants to what extent they believed the following statements to be true: "Climate change is caused primarily by human action". Their response was measured on a visual analogue scale ranging from *I am 100% certain this is false* (-100) to *I am 100% certain this is true* (100) with *I don't know* in the middle (0).

Perceived scientific consensus was measured in a similar way, once at the start of the experiment and once after the consensus reasoning manipulation and news article. We asked participants what they thought was the percentage of climate scientists who agreed that climate change is caused primarily by human action. Their response was measured on a scale ranging from 0 to 100%.

The manipulation check consisted of asking participants what steps they take to evaluate claims. Three text boxes were provided to them, and at least one of these needed to be used. Responses were coded to identify whether consensus (or something similar) was mentioned. The coding procedure was tested in the pilot study.

Other, exploratory measures, including secondary outcomes such as worry about climate change, support for policy aimed at tackling climate change, and the intention to reduce one's own CO_2 footprint, can be found on OSF (see Additional Measures at https://osf.io/qx23b/).

Data analysis

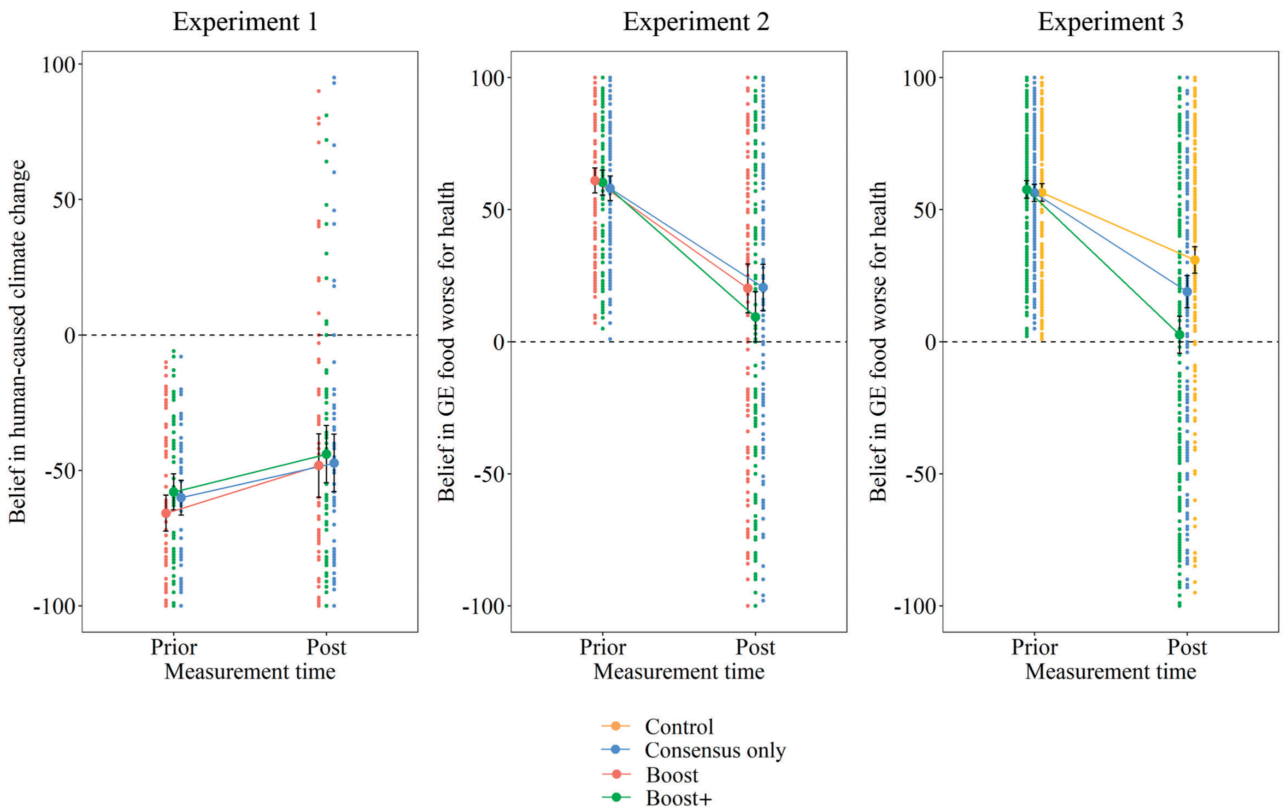
We conducted two ANCOVA, with posterior belief in human-caused climate change as the dependent variable, condition as independent variable, and prior belief as covariate. First, we compared the combined boost conditions to the consensus-only condition (hypothesis 1). Second, we compared the two boost conditions to each other (hypothesis 2). Standard assumptions for linear models were checked, and, where necessary, additional robust ANCOVAs were conducted. In all confirmatory analyses, and in accordance with the preregistrations, model outliers > 3 *SD* were removed. This did not substantially alter the results. In contrast to the preregistrations, we computed Bayes factors (using Bayesian ANCOVA, prior *r* scale = 0.5, 10,000 Markov chain Monte Carlo iterations) not only when the results of the hypotheses tests were not statistically significant, but also when they did yield significant results.

Results

We conducted a manipulation check and, as expected, when asked how they evaluate claims, participants in the boost conditions mentioned consensus more often (18.24%) than participants in the consensus-only condition (2.70%; $\chi^2(1, N = 222) = 9.17$, $p = .002$).

We did not find support for our hypothesis that boosting consensus reasoning leads to higher belief in human-caused climate change. Specifically, an ANCOVA comparing the combined boost conditions ($M = -50.26$, $SD = 43.58$) to the consensus-only condition ($M = -51.21$, $SD = 39.82$) indicated that the main effect of condition on posterior belief in human-caused climate change was not significant, $F(1, 212) = 0.46$, $p = .497$, $\eta_p^2 = .002$, 90% CI [.000, .023], $BF_{10} = 0.19$. The difference between the boost+ ($M = -47.44$, $SD = 40.58$) and boost ($M = -51.16$, $SD = 48.60$) conditions was also not significant, $F(1, 141) = 1.73$, $p = .191$, $\eta_p^2 = .012$, 90% CI [.000, .058], $BF_{10} = 0.39$. Because the model residuals indicated poor model fit, we conducted additional bootstrapped, robust ANCOVAs. These yielded the same results (all *p*s for both robust ANCOVAs and levels of covariate > .215; for more details, see Supplementary Analyses on OSF at https://osf.io/5xnt4/). We conducted an exploratory, omnibus ANCOVA similar to the main analysis, but now comparing all three conditions separately. The omnibus ANCOVA was also not significant, $F(2, 218) = 0.72$, $p = .486$, $\eta_p^2 = .007$, 90% CI [.000, .029]. See left panel of Figure 2 for an overview of the results.

Figure 2 Prior and Posterior Belief per Experiment per Condition



Note. In Experiment 1, higher scores indicate more accurate beliefs, while in Experiments 2 and 3 lower scores indicate more accurate beliefs. Small dots represent individual observations, bigger dots with error bars represent mean scores and 95% confidence intervals (CIs), and lines illustrate the differences between prior and posterior mean scores. Plots, including means and CIs, were created with complete samples, before model outliers were removed.

One potential explanation for the ineffectiveness of the boosts to aid in correcting the misperception is that they did not affect the gateway belief (participants' perception of the scientific consensus). We were able to investigate this explanation, because perceived consensus was also measured at the start and end of the experiment (for means and SDs, see Appendix D). The omnibus ANCOVA, with posterior perceived consensus as the dependent variable, condition as the independent variable, and prior perceived consensus as covariate, yielded no significant effect, $F(2, 218) = 0.42$, $p = .655$, $\eta_p^2 = .004$, 90% CI [.000, .021], indicating that the boosts did not have an effect on changes in perceived scientific consensus compared to the consensus-only condition (though note that there was a significant difference between prior and posterior perceived consensus overall; see Supplementary Analyses on OSF).

An explanation for the ineffectiveness of the boosts to affect either the misperception or the perceived consensus is that participants' anti-science view hindered them from accepting the science-based boosting strategy for claim evaluation. This notion was supported by the fact that the boosts were less effective in eliciting consensus reasoning in the experiment than they were in the pilot study that we had conducted with people most of whom did believe in human-caused climate change. Moreover, we found a positive, point biserial correlation in the combined boost conditions between trust in climate scientists and the score on the manipulation check (consensus mentioned: $r(146) = .32$, $p < .001$). Post hoc, we think that anti-science views may have prevented our boosts from working properly. This may be specific to climate change communication, as trust in climate scientists in the US is low, particularly among those who are likely to reject human-caused climate change (Pew Research Center, 2016). The data reflect this low trust, with participants scoring below the mid-point ($M = 3.22$, $SD = 1.68$) on a 7-point scale of trust in climate scientists. This means that our current approach may not be suitable for addressing misperceptions on climate change, but may still be suitable for a topic where trust in scientists is higher.

Experiment 2 – Genetically Engineered Food

Based on the null results of the first experiment, and the finding that climate scientists were viewed as relatively untrustworthy, we decided to change the topic of the following experiment. In Experiment 2 we addressed the misperception that genetically engineered (GE) food is worse for health than non-GE food.

Method

The experiment was highly similar to Experiment 1, except for the topic of misperception. A second difference consisted of a follow-up measure of participants' belief two weeks after participation in the experiment.

Participants

Again, participants were recruited following a sequential sampling procedure. Following the results of the first experiment, we decided to focus the sequential sampling procedure on hypothesis 1 (comparing the combined boost conditions with the consensus-only condition). Therefore, we planned to continue data collection until there was moderate evidence (1/6 > BF_{10} > 6) in favor of or against hypothesis 1 and slightly less substantial evidence (1/3 > BF_{10} > 3) in favor of or against hypothesis 2. We started checking the BFs at 50% of the maximum *N* (225 participants) and decided to check them after every set of 75 new participants. As the desired level of evidence was never obtained, we recruited participants until the maximum *N* was reached (see online Supplemental Material for more detail).

All participants were screened such that at the start of the experiment they held the belief that GE food is worse for health than non-GE food (final *N* = 442; 51.13% female, M_{Age} = 38.54, SD_{Age} = 13.06).

Materials and procedure

The news article containing the consensus statement in Experiment 2 (313 words) discussed a new, fungus-resistant GE banana and was adapted from a news article from Science (Stokstad, 2017). The consensus statement in the news article was based on research from the Pew Research Center on scientists' views on genetically modified foods (Pew Research Center, 2015), presenting the conclusion: *In 2014 already, a survey showed that there is a scientific consensus on the safety of genetically engineered food. Dr. Cary Funk from the Pew Research Center: "92% of working Ph.D. biomedical scientists said it is as safe to eat genetically engineered foods as it is to eat non-GE foods"*.

Participants were invited to the follow-up study approximately 14 days after participation in the initial experiment. A total of 370 participants (448 invited, retention rate ~ 83%) completed the follow-up study, of whom 365 were retained after exclusions. These participants completed the follow-up study on average 14.03 days (*SD* = 0.42, min = 12.86, max = 15.94) after participation in the initial experiment. The follow-up study consisted of two measures: a repetition of the belief measure and a repetition of the perceived consensus measure.

Measures

Belief in the GE-misperception was measured by asking participants to what extent they believed the following statement to be true: "Genetically engineered (GE) food products are worse for health than non-GE food products". Again, their response was measured on a visual analogue scale ranging from *I am 100% certain this is false* (-100) to *I am 100% certain this is true* (100) with *I don't know* in the middle (0). Note that in contrast to Experiment 1, a misperception is indicated by a positive score. Perceived scientific consensus was measured by asking participants to estimate the consensus among biomedical scientists.

Results

Again, the results of the manipulation check demonstrated that the boosts were effective in eliciting consensus reasoning in claim evaluation compared to the consensus-only condition, $\chi^2(1, N = 442) = 50.28$, $p < .001$. Moreover, the manipulation check also indicated that the boosts were more effective than in the first experiment (18.24% of participants in the boost conditions mentioned consensus in Experiment 1 vs 35.81% in Experiment 2), supporting our assumption that individuals who are skeptical about the safety of GE food are more receptive to the boosts than those who deny human-caused climate change. Possibly related, overall there was a relatively high degree of trust in biomedical scientists as a source of information about GE food ($M = 4.66$, $SD = 1.55$).

The hypothesis that boosting consensus reasoning leads to lower belief in GE food being worse for health received tentative support in Experiment 2. First, the main effect of boosting consensus reasoning on posterior belief, comparing the combined boost conditions ($M = 14.84$, $SD = 58.06$) to the consensus-only condition ($M = 20.51$, $SD = 53.57$), was not significant, $F(1, 439) = 2.91$, $p = .089$, $\eta_p^2 = .007$, 90% CI [.000, .025], $BF_{10} = 0.44$. There was also no significant difference between the boost+ ($M = 9.44$, $SD = 58.56$) and the boost ($M = 20.17$, $SD = 57.25$) condition on posterior belief, $F(1, 293) = 3.03$, $p = .083$, $\eta_p^2 = .010$, 90% CI [.000, .037], $BF_{10} = 0.54$. However, when we explored the remaining comparisons between conditions, a significant difference in posterior belief between the boost+ and the consensus-only condition emerged, Tukey-corrected $p = .048$, $\eta_p^2 = .018$, 90% CI [.001, .051]; participants in the boost+ condition reported lower belief in GE food being worse for health than participants in the consensus-only condition. The BF, however, indicated only anecdotal evidence in favor of the alternative model ($BF_{10} = 1.52$). At the time of the follow-up measure, two weeks later, this difference between the boost+ ($M = 25.74$, $SD = 49.92$) and consensus-only ($M = 25.38$, $SD = 51.16$) conditions was no longer statistically significant, Tukey-corrected $p = .774$, $\eta_p^2 = .002$, 90% CI [.000, .022].

Experiment 3 – GE Food Replicated

The results of Experiment 2 suggested that there may be some potential to boosting both understanding and identification of scientific consensus, but we did not yet find convincing evidence to either support or oppose its effectiveness. One explanation for these tentative findings could be a lack of power. We addressed this issue in Experiment 3 by conducting a high-powered replication.

Method

We retained the boost+ and consensus-only conditions, to test the effectiveness of boosting consensus reasoning over not boosting consensus reasoning in the presence of a consensus statement. The short boost condition was dropped, because the results from the previous experiment indicated that this boost, if anything, would be less effective than the boost+. Instead, we added a control condition in which participants neither received a boost nor read a consensus statement. This allowed us to test whether the consensus statement was effective in correcting the misperception in the first place. The follow-up measure was dropped, to reserve all our resources for testing the immediate effects with high power. We hypothesized that when participants would be exposed to the consensus statement, the boost+ would lead to lower posterior belief in GE food being worse for health than no boost. Second, in the two previous experiments we had found quite substantial differences between prior and posterior beliefs in general (though this can partly be explained by regression to the mean). Based on this, we hypothesized that when participants did not receive a boost, exposing them to the consensus statement would lead to lower posterior belief in GE food being worse for health than not exposing them to the consensus statement.

Participants

The recruitment procedure for Experiment 3 was similar to that of Experiment 2, except that no sequential sampling procedure was employed. Instead, we conducted an a priori power analysis based on the comparison between the boost+ and consensus-only conditions of Experiment 2 (see online Supplemental Material; final $N = 854$; 65.81% female, $M_{Age} = 35.90$, $SD_{Age} = 12.92$).

Materials and procedure

Participants in the control condition read the same news article as in the other conditions, but the paragraph about the consensus was replaced with a paragraph discussing a field trial that had been conducted with different versions of the GE banana.

Measures

In contrast to the first two experiments, the manipulation check was conducted using an automated R script (see the R script on OSF for the automated procedure).

Results

The manipulation check indicated that the boost+ increased consensus reasoning in claim evaluation, compared to the consensus-only, $\chi^2(1, n = 562) = 71.86$, $p < .001$, and control conditions, $\chi^2(1, n = 567) = 65.33$, $p < .001$.

We found strong support in the data for both hypotheses. First, we found the expected effect on belief of the boost+ over no boost in the presence of a consensus statement. The difference between posterior belief in the boost+ condition ($M = 2.62$, $SD = 58.59$)

and posterior belief in the consensus-only condition (M = 18.93, SD = 51.80) was significant, $F(1, 559) = 16.90$, $p < .001$, $\eta_p^2 = .029$, 90% CI [.011, .056], BF_{10} = 309.98. This effect of boosting consensus reasoning, reflected in a Cohen's d of -0.35 (95% CI [-0.52, -0.18]; calculated using the prior-post difference scores), is similar to the same effect in Experiment 2 (Cohen's d = -0.27, 95% CI [-0.50, -0.04]), is very close to the median effect size in communication research (Rains et al., 2018) and can be characterized according to convention as small-to-medium (Cohen, 1988). The second expected effect, that participants who were presented with the consensus statement would adjust their belief more than participants who read the news article without the consensus statement, measured by comparing posterior belief in the consensus-only condition to the control condition (M = 30.91, SD = 43.66), was also significant, $F(1, 571) = 10.58$, $p = .001$, $\eta_p^2 = .018$, 90% CI [.004, .040], BF_{10} = 15.45. This effect of consensus communication, reflected in a Cohen's d of -0.29 (95% CI [-0.46, -0.13]; again calculated using the prior-post difference scores), is quite similar in size to the effect of boosting consensus reasoning. Thus, the data provide strong evidence of the effectiveness of communicating the scientific consensus to correct a misperception regarding GE food, as well as of strengthening the corrective effect of the consensus by boosting individuals' consensus reasoning.

4

We conducted additional, exploratory analyses to investigate effects of the boost+ and consensus information on perceived consensus. We found significant differences between the boost+ (M = 74.45, SD = 25.82) and control (M = 51.52, SD = 25.50) conditions, Tukey-corrected $p < .001$, $\eta_p^2 = .199$, 90% CI [.152, .245], and between the consensus-only (M = 71.20, SD = 25.67) and control conditions, Tukey-corrected $p < .001$, $\eta_p^2 = .144$, 90% CI [.102, .187], indicating that both participants in the boost+ and consensus-only condition increased their estimate of the scientific consensus much more than participants in the control condition. There was no significant difference between the boost+ and consensus-only conditions on perceived consensus, Tukey-corrected $p = .145$, $\eta_p^2 = .005$, 90% CI [.000, .020].

Discussion

Holding on to misperceptions in the face of overwhelming scientific evidence can be harmful to an individual and to society, but correcting those misperceptions can be hard. In three experiments we investigated a strategy aimed at correcting misperceptions: boosting consensus reasoning. We explained the value of scientific consensus and provided steps to identify scientific consensus when evaluating the veracity of a claim. In the case of climate change, we found moderate evidence against the effectiveness of an extensive boost (the boost+) to correct a misperception (BF_{10} = 0.18, increase in belief in true statement of d = 0.04), whereas a high-powered experiment about GE food yielded extreme evidence in favor of boosting consensus reasoning to aid participants to come to an accurate belief (BF_{10} = 309.98; decrease in belief in false statement of d = -0.35).

There could be multiple reasons for these differing results. First, trust in climate scientists in the US is low (Pew Research Center, 2016), while biomedical scientists might relatively be trusted more. This raises the possibility that boosting consensus reasoning is less effective in situations where there is low trust in the relevant experts. Our data support this explanation, showing that climate scientists were trusted less than biomedical scientists as a source of information about their respective fields. Relatedly, this difference in trust might also be reflected in the sources of the consensus statements quoted in the news articles that we used as stimulus material, potentially yielding lower trust in the source of the climate consensus than the source of the GE food consensus. Another explanation could be that misperceptions related to climate change are simply more resistant to correction than misperceptions about GE food, for instance because they are more crystallized. Climate change is a highly politicized topic, suffering from decades of strategic use of misinformation (Cook, 2016), which may have resulted in those individuals who hold misperceptions becoming resistant to new information. Our data also support this second explanation, with the overall decrease in false belief being smaller in the experiment about climate change than in the experiments about GE food.

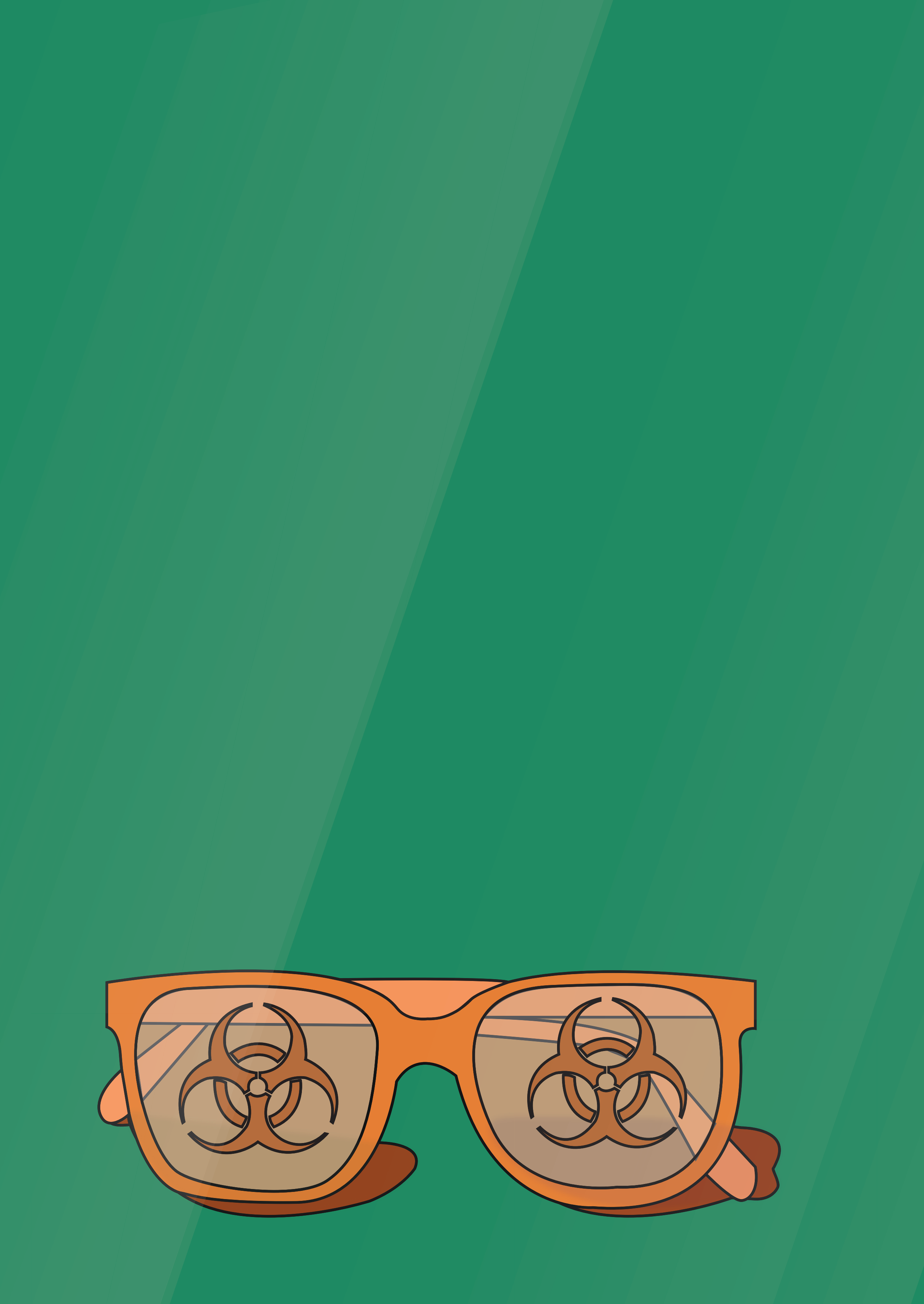
A third explanation could be that the perceived scientific consensus was already higher at the start of the climate change experiment than it was at the start of the GE experiments. Being more aware of the scientific consensus about human-caused climate change, these participants might have become more resistant to influence of consensus knowledge on their personal beliefs. This explanation is partly supported by our data, which show that participants in the climate change experiment had a higher perceived consensus at the start of the experiment than participants in the GE food experiments. They did, however, substantially increase their estimate during the experiment, in contrast to what would be expected if they were resistant to consensus messaging in general. Finally, it could be that we did not have enough statistical power in the climate change experiment to find a 'true' difference between the boost+ and the consensus-only condition. The BF indicated only moderate evidence against the effectiveness of the boost+ in the climate change experiment, which does not convincingly rule out an effect. Even if there existed a true effect in our sample of climate change deniers similarly sized to the one we found in Experiment 3 about GE food, then the experiment about climate change was underpowered (achieved power ~55%). Of course, a combination of these four explanations may also be at play here.

Apart from enhancing the corrective effect of consensus communication, there are two main arguments for boosting consensus reasoning. First, boosting consensus reasoning might not only help individuals to recognize a true scientific consensus, but it might also help them to identify a false consensus. People are notoriously poor at distinguishing between true and false consensuses (Yousif et al., 2019). Boosting consensus reasoning empowers individuals to identify misinformation in the form of a false consensus, by looking at the source of the consensus claim and the expertise of the individuals making up the consensus. A single scientist stating that GE food is bad for your health, for example, should not be persuasive to boosted individuals. Second, there is an ethical advantage to boosting over only communicating the consensus, namely that its goal is to empower individuals (Hertwig & Grüne-Yanoff, 2017). Consensus communication is often criticized on the grounds that it invokes scientists' authority as a means of persuasion (Pearce et al., 2015). Conversely, boosting is meant not to persuade, but to empower individuals to be able to understand and make the best use of the available information regarding a scientific consensus, whether that consensus is in line with their preferred belief or not.

Many questions remain regarding boosting consensus reasoning. First, our boost+ manipulation was multifaceted: it discussed how scientific consensus develops and why it is useful in evaluating claims, it presented steps explaining how to recognize a true consensus, and it included a practice session with feedback regarding how to apply these steps. From the current work it is unclear which part (or combination of parts) of the manipulation is responsible for the corrective effect. Future research could examine what specifically drove our boosting effect, as well as whether parts of it (such as explaining the value of scientific consensus) could also be used as a more direct means of persuasion. Second, regarding the generalizability of the findings, we investigated boosting consensus reasoning in the context of only two topics, with mixed results. Relatedly, we recruited participants from an online crowdsourcing platform for research. Prolific allowed us to sample from the population of interest (individuals holding misperceptions), but it is unclear if these participants are representative of the general population of misperception-holders out there. Therefore, much remains to be learned about the generalizability of the findings, both regarding different topics of misperception and the individuals holding the misperceptions. Third, as mentioned, boosting could help individuals identify misinformation, such as a false consensus (Cook, 2016). Future research could investigate this possibility by employing a similar design to the current research, but testing a message communicating a false consensus. Finally, the current research was quite straightforward in that participants had the opportunity to apply their boosted consensus reasoning skill immediately. The results of the two-week follow-up measure in Experiment 2 indicated no clear difference between beliefs in the boost+ and consensus-only conditions. We are hesitant in interpreting this result, because the second experiment appeared to be underpowered to detect an effect of the boost+ compared to consensus-only, especially at follow-up. The question remains whether the boost in consensus reasoning is durable, allowing consensus reasoning to be activated later in time, or instead deteriorates.

Although the focus of the current work was on boosting consensus reasoning, it also demonstrates the corrective effect of consensus communication by itself in the case of genetically engineered food. Previous research has demonstrated that consensus messaging can change beliefs about genetically modified food in the general population (Kerr & Wilson, 2018). Here we show that consensus messaging can also correct misperceptions in this domain. While previous research has yielded promising results about reducing belief in misperceptions in the general population (e.g., about a vaccine-autism link, see van der Linden, Clarke, et al., 2015), we believe this is the first experimental work that tests consensus messaging in a sample of misperception-holders.

To conclude, the current work extends existing research by demonstrating that empowering individuals who hold misperceptions to use scientific consensus in deciding whether or not something is true can help to correct these false beliefs. Moreover, it provides evidence that communicating scientific consensus is not only an effective strategy to strengthen accurate beliefs, as seen in previous research, but can also be used to correct misperceptions. These findings support a strategy of open communication about the process of reaching a scientific consensus. There is much to be won, considering that cues signaling the existence of consensus in relevant news content are very rare (Merkley, 2020). With a public deficient in knowledge about the scientific consensus on important societal topics, communicating the consensus itself is a promising place to start. And with scientists deficient in communication about the scientific process, consensus communication could be paired with boosting consensus reasoning.



CHAPTER 5

Investigating and Improving the Accuracy of US Citizens' Beliefs About the COVID-19 Pandemic: Longitudinal Survey Study

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Abstract

The COVID-19 infodemic, a surge of information and misinformation, has sparked worry about the public's perception of the coronavirus pandemic. The objective of this study was to gain insight into public beliefs about the novel coronavirus and COVID-19 and to test whether a short intervention could improve people's belief accuracy. We conducted a 4-week longitudinal study among US citizens, starting on April 27, 2020 . Each week, we measured participants' belief accuracy related to the coronavirus and COVID-19. Furthermore, half of the participants were exposed to an intervention aimed at increasing belief accuracy. Mean scores of belief accuracy were high for all waves, with scores reflecting low belief in false statements and high belief in true statements. Trust in scientists, political orientation, and the primary news source were associated with belief accuracy. The intervention did not significantly improve belief accuracy. Thus, the supposed infodemic was not reflected in US citizens' beliefs about the COVID-19 pandemic. Most people were quite able to figure out the facts in these relatively early days of the crisis, calling into question the prevalence of misinformation and the public's susceptibility to misinformation.

Keywords: infodemic, infodemiology, misinformation, COVID-19 pandemic, belief accuracy, boosting, trust in scientists, political orientation, media use

Introduction

Public health crises tend to go hand in hand with information crises. The COVID-19 pandemic, which is taking many lives and is hospitalizing hundreds of thousands of people globally, is no exception. In the wake of the COVID-19 pandemic, we are seeing signs of a misinformation pandemic. Around the first peak of the coronavirus outbreak in the US, the country with the highest COVID-19 death toll (Rahim, 2020), about two-thirds of Americans said they had been exposed to at least some made-up news and information related to the virus (Mitchell et al., 2020). Misinformation about the pandemic seems to have proliferated quickly, especially on social media (Frenkel et al., 2020). The World Health Organization (WHO) has labelled this surge of (mis)information about the COVID-19 pandemic an 'infodemic' (World Health Organization, 2020).

Countries and social media platforms are trying to tackle this infodemic in a number of ways. Several social media platforms, including Facebook and Twitter, have implemented new procedures to remove or label false and misleading content (Allyn, 2020; T. Romm, 2020). However, with the vast number of posts made to these platforms every day and the platforms' fear of infringing on free speech, the success of these procedures is limited (e.g., Avaaz, 2020). A second strategy consists of surfacing trusted content, for instance by referring people with questions to the WHO or national health agencies, such as the Centers for Disease Control and Prevention (CDC) in the US and the National Epidemiology Center (CENEPI) in Brazil. This approach might be hindered by government officials, including US president Donald Trump and Brazilian president Jair Bolsonaro, actually contributing to the spread of misinformation (e.g., Londoño, 2020; Milman, 2020). Considering this apparent infodemic, are people able to distinguish facts from fiction? And what correlates might enable or disable them in forming accurate beliefs?

One promising approach to limiting the effects of misinformation was already on the rise before the COVID-19 pandemic: increasing misinformation resistance through educational interventions. A substantial number of countries have implemented educational interventions, primarily focused on 'media literacy' (Funke & Flamini, 2020), which can be understood as the ability to access, analyze, evaluate and communicate messages in a variety of forms (Potter, 2010). The Swedish Civil Contingencies Agency, for instance, has included a section about misinformation in its public emergency preparedness brochure, advising Swedes to be aware of the aim of information and check the source of information, among others (Swedish Civil Contingencies Agency, n.d.). Similarly, Facebook tries to help its users recognize misinformation by providing 10 tips (Facebook, 2020). One advantage of such a focus on media literacy is that it can help prevent problems with misinformation, instead of having to correct false beliefs after they have taken hold. Previous media literacy research, with interventions focusing on identification of misinformation, has yielded promising results indicating that some interventions can reduce the perceived accuracy of misinformation (Guess, Lerner, et al., 2020; Hameleers, 2020). Other research highlights the difficulties in crafting media literacy interventions (Vraga et al., 2020). Can these types of interventions, focusing on empowerment of media consumers, help individuals deal with the supposed COVID-19 infodemic?

Our approach focuses on helping individuals figure out what is true and what is false, considering false such beliefs about factual matters that are not supported by clear evidence and expert opinion (Nyhan & Reifler, 2010). We test an intervention that empowers people to search for and identify scientific consensus. Communicating scientific consensus (i.e. a high degree of agreement between scientists) is effective in eliciting scientifically accurate beliefs (Cook, 2016). This effectiveness is described in the Gateway Belief Model, which states that people's perceived scientific consensus functions as a gateway to their personal factual beliefs (van der Linden, Leiserowitz, et al., 2015, 2019). Here, we focus on empowering individuals to search for and identify scientific consensus, because this approach is more flexible than communicating a scientific consensus on every single issue.

The current strategy is considered a 'boosting' approach. Boosting encompasses interventions targeting competence rather than immediate behavior (Hertwig & Grüne-Yanoff, 2017). In line with this, our intervention focuses on improving people's skills to form accurate beliefs, instead of altering the external context within which people form beliefs. In addition, our boosting approach can be considered an educational intervention, just like media literacy interventions. However, compared to media literacy interventions that target the identification of misinformation, boosting 'consensus reasoning' is not dependent on being exposed to misinformation. One can investigate any claim, true or false, from any source.

This study had two main goals. One involved an exploratory (not preregistered) investigation to gain insight into the effects of the supposed infodemic on individuals' belief accuracy in times of crisis, and to investigate potential correlates of belief accuracy. The second goal was a preregistered test of the boosting intervention aimed at increasing belief accuracy. Accordingly, we hypothesized our intervention to lead to more accurate beliefs about the COVID-19 pandemic than control (the complete preregistration can be found on the Open Science Framework (OSF). The research was conducted online, recruiting a balanced sample of the US population. We decided to focus on the US, because this is arguably the country worst hit by the COVID-19 pandemic. Using a longitudinal design, measuring beliefs about the pandemic over four weeks just after daily confirmed COVID-19 deaths had peaked at over 4000, allowed us to investigate and intervene on belief formation in the relatively early days of the pandemic. All data and material are available on the project page on the OSF.

Methods

Recruitment

We used Prolific, a UK-based online crowdsourcing platform that connects researchers to participants, to collect data from US citizens over a four-week period. Prolific has been demonstrated to yield high-quality data and more diverse participants than student samples or other major crowdsourcing platforms (Peer et al., 2017). In addition, it allowed for recruitment balanced on age, gender, and ethnicity to approximate the US general public (via stratification, using US census data; United States Census Bureau, 2019). Recruitment for the initial baseline wave started on April 27.

A total of 1212 individuals participated in the study at baseline (T0), for which they received £0.45 (roughly $0.56) A total of 1089 individuals participated in the first follow-up wave (T1), 1070 individuals participated in the second follow-up wave (T2), and 1028 individuals participated in the final wave (T3; see Table 1 for total sample size, exclusions, and final sample size per wave). Participants received £0.33 (roughly $0.41) for participation per follow-up survey. Each of the waves was separated by approximately one week ($mean_{T0\text{-}T1}$=6.98 days, $SD_{T0\text{-}T1}$=14.92 hours; $mean_{T1\text{-}T2}$=7.01 days, $SD_{T1\text{-}T2}$=12.72 hours; $mean_{T2\text{-}T3}$=7.06 days, $SD_{T2\text{-}T3}$=13.18 hours). The sample size was determined by the available resources.

Table 1 Total Sample Size, Exclusions, and Final Sample Size per Wave

Wave	Sample	N
T0: April 27 – April 29	Total sample	1212
	Excluded	10
	Final sample	1202
T1: May 4 – May 7	Total sample	1089
	Excluded	11
	Final sample	1078 (RT = 89.7%)
T2: May 11 – May 14	Total sample	1070
	Excluded	3
	Final sample	1067 (RT = 88.8%)
T3: May 18 – May 21	Total sample	1028
	Excluded	6
	Final sample	1022 (RT = 85%)

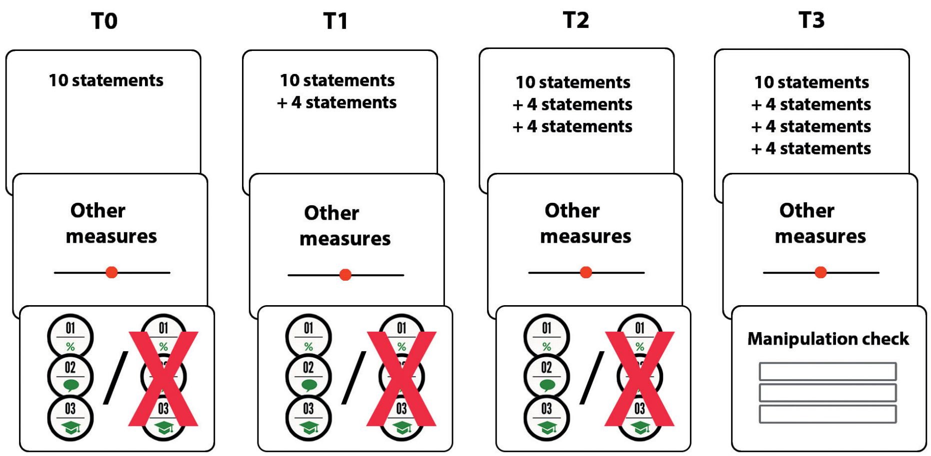
Note. RT = Retention rate, based on final samples of T0 and respective wave. Total sample sizes of follow-up waves were counted excluding two participants who should have been excluded but had been allowed to participate in the follow-up waves due to a technical error. More details on exclusions can be found in Statistical Analysis: Data exclusion, below.

This study is part of a research project that was reviewed and approved by the Ethics Committee Social Science at Radboud University (ref. ECSW-2018-056).

Procedure

Participants were randomly assigned to either receive the intervention (the boost condition) or no intervention (control condition). All surveys started with the measure of belief accuracy, for which participants were presented with 10 (T0), 14 (T1), 18 (T2), or 22 (T3) statements about the coronavirus and COVID-19 (see Figure 1). Participants indicated to what extent they believed each statement to be true. An attention check was included among these statements (see Appendix E). Subsequently, participants reported their behavior aimed at preventing the spread of the coronavirus and completed the other measures. The boosting intervention, an infographic presenting three steps that can be used to evaluate a claim, was included at the end of T0, T1, and T2. Only participants in the boost condition were presented with the infographic, allowing them to apply their boosted consensus reasoning skill in the week leading up to the next wave. At T3, all participants completed a manipulation check. At the end of T0, all participants entered demographic information and completed a seriousness check (see Appendix E). All surveys took about 3-6 minutes.

Figure 1 Flowchart of the Main Elements of the Procedure per Wave



Note. Participants first completed the measure of belief accuracy, then completed other measures, and finally were exposed to the intervention or not. At T3 participants completed a manipulation check. The bottom panels of the first three columns display the intervention condition (left; infographic) and the control condition (right; no intervention).

Materials and Measures

Belief Accuracy

The key dependent variable was the accuracy of participants' beliefs related to the COVID-19 pandemic. This variable consisted of responses to a number of statements about the pandemic, which were sourced from preprints of early research on public perceptions of COVID-19 (e.g., Singh et al., 2020), public health agencies and medical institutes (e.g., WHO), media tracking organizations (e.g., NewsGuard), and expert reports in established media (e.g., CNBC; comprehensive list available in Appendix F). Only statements based on scientific claims were included, to make sure that there was compelling evidence that the claims were either true or false.

At baseline, participants were exposed to 10 statements, of which five were scientifically accurate (e.g., 'Fever is one of the symptoms of COVID-19') and five were at odds with the best available evidence (e.g., 'Radiation from 5G cell towers is helping spread the coronavirus'). Participants responded by indicating a statement was either false, probably false, they did not know, probably true, or true. In each subsequent wave, four new statements were added to the list of statements (two accurate ones and two inaccurate ones). This allowed us to keep the belief accuracy measure current, reflecting contemporary insights and discussion points. The order of the statements was randomized per participant and varied per wave.

A belief accuracy score was calculated by converting the response to each statement to a number reflecting how accurate the response was, counting a correct judgment as 1, an incorrect judgment as -1. A less certain but correct 'probably true' or 'probably false' counted as 0.5, an incorrect one as -0.5. Finally, a 'Don't know' was counted as 0. Average scores were calculated per wave per participant, resulting in a repeated measure of belief accuracy. Internal consistency was acceptable to good across the four waves (McDonald's ω_t between 0.75 and 0.87 in all waves).

Coronavirus-related Behavior

Coronavirus-related behavior aimed at preventing the coronavirus from spreading was measured by asking participants to indicate their agreement with three statements. The statements were "To prevent the coronavirus from spreading…" i) "I wash my hands frequently", ii) "I try to stay at home / limit the times I go out", and iii) "I practice social distancing (also referred to as 'physical distancing') in case I go out," all measured on a scale from 1 (strongly disagree) to 7 (strongly agree). Scores were averaged per wave per participant. Internal consistency was acceptable to good across the four waves (McDonald's ω_t between 0.77 and 0.83 in all waves).

Additional Measures
Trust in scientists was measured in all four waves with responses to the statement "I trust scientists as a source of information about the coronavirus". Participants responded on a 7-point scale ranging from "Strongly disagree" to "Strongly agree".

Participants' primary news source for information about the COVID-19 pandemic was identified by asking them at T0 what their main source of news about the coronavirus was. Participants could choose one option from a list of 11 news sources, based on data from the Pew Research Center on Americans' news habits (Pew Research Center, 2020).

Finally, we included a manipulation check at T3. This consisted of asking participants how they evaluated the truthfulness of the statements about the coronavirus and coronavirus disease in the study over the past weeks. We asked them to name the steps that they took to evaluate the claims in three open text boxes, of which at least one had to be used. These answers were coded by the first author to indicate whether they mention consensus (or something similar) or not. A second coder coded a random subset of 120 answers, with Krippendorff's alpha indicating good (α=0.85) inter-rater reliability. Therefore, the complete coding from the first author was used in the analyses.

Not all measures included in the study are listed here, because not all measures are relevant here. Please see the material on the project page on the OSF for the remaining measures.

Intervention
The boosting intervention that was included at the end of T0, T1, and T2 consisted of a short infographic that was aimed at empowering participants to use scientific consensus when evaluating claims related to the COVID-19 pandemic. The infographic set out three steps that can be used to evaluate a claim: i) searching for a statement indicating consensus among scientists, ii) checking the source of this consensus statement, and iii) evaluating the expertise of the consensus. The infographic can be found in Appendix G. Participants in the control condition were not exposed to the infographic.

Demographics
Demographics political orientation, age, gender, ethnicity, and education were asked at T0. Political orientation was measured by combining political identity (Strong Democrat, Democrat, Independent Lean Democrat, Independent, Independent Lean Republican, Republican, or Strong Republican) and political ideology (Very Liberal, Liberal, Moderate, Conservative, or Very Conservative), into one numeric, standardized measure centered on 0 (moderate/Independent; based on Kahan (2013)).

Statistical Analysis

Data Exclusion

First, we removed one of two duplicate responses at T1 and excluded all responses of one participant with three varying responses at T3.

As preregistered, participants who failed the attention check at T0 were excluded and replaced (n=8; including two who had been allowed to participate in the follow-up waves due to a technical error). If a participant failed one of the attention checks in the subsequent waves, data from that wave was not included in the analyses (n_{T1}=5, n_{T2}=2, n_{T3}=5), but other surveys in which the attention check was passed were retained. Participants who indicated at the seriousness check at T0 that their data should not be used were excluded from further participation, their data was not used, but they were not replaced (n=2). No participants completed T0 in less than one minute, but if a participant completed a subsequent wave in less than one minute, data from that survey was not included in the analyses (n_{T1}=6, n_{T2}=1, n_{T3}=0). Other waves in which the one-minute threshold was passed were retained. See Table 1 for an overview of all participants and exclusions per wave.

Exploratory (Not Preregistered) Analyses

General increase in belief accuracy over time was explored using linear mixed modeling for each set of statements, with wave as predictor, controlling for political orientation, and including a random intercept per participant. The relationship between belief accuracy and coronavirus-related behavior was explored with correlations for each wave. The relationship of belief accuracy with trust in scientists (at T0), political orientation, and primary news source was explored using mixed modeling, controlling for wave, age, gender, education, and ethnicity. The interaction term between trust and political orientation was included in the model. The five most chosen news sources (CNN, Fox News, NPR, social media sites, and The New York Times, excluding the option "Other sources") were included as dummy coded variables. Finally, we included a random intercept and a random slope for wave per participant. Mixed modeling was performed with the lme4 package (Bates et al., 2015) in R (R Core Team, 2019). The models were examined using likelihood ratio tests (LRT), using the package lmerTest (Kuznetsova et al., 2017).

Preregistered Analysis

The hypothesis that our intervention would lead to more accurate beliefs than control was also tested using linear mixed modeling. The experimental condition (intervention vs. control) and wave, and the interaction between condition and wave, were included as predictors in the model. Political orientation was included as a covariate, because beliefs about the COVID-19 pandemic are related to political ideology (van Holm et al., 2020), and a random intercept and a random slope for wave were included per participant. The hypothesis was tested by comparing the full model, with the interaction between condition and wave, to a model without this interaction effect. We used the PBmodcomp function from package pbkrtest (Halekoh & Højsgaard, 2014) for parametric bootstrapping (10,000 simulations).

Results

Participants

The final sample roughly reflects US census data (United States Census Bureau, 2019) on gender, age, and ethnicity, indicating that the balanced sampling worked well. See Table 2 for more details.

Table 2 Participant Descriptives

Descriptive	Demographic characteristic	# in sample	% in sample	% Census
Gender	Female	604	50.2%	51.3%
	Male	587	48.8%	48.7%
	Other	11	0.9%	N/A
Age	18 to 24 years	164	13.6%	11.9%
	25 to 34 years	243	20.2%	17.9%
	35 to 44 years	209	17.4%	16.4%
	45 to 54 years	199	16.6%	16.0%
	55 to 64 years	232	19.3%	16.6%
	65 to 74 years	139	11.6%	12.4%
	75 and older	16	1.3%	8.8%
Ethnicity	White	918	76.4%	73.6%
	Black	158	13.1%	12.5%
	Asian	79	6.6%	5.9%
	Mixed	30	2.5%	2.5%
	Other	17	1.4%	5.5%

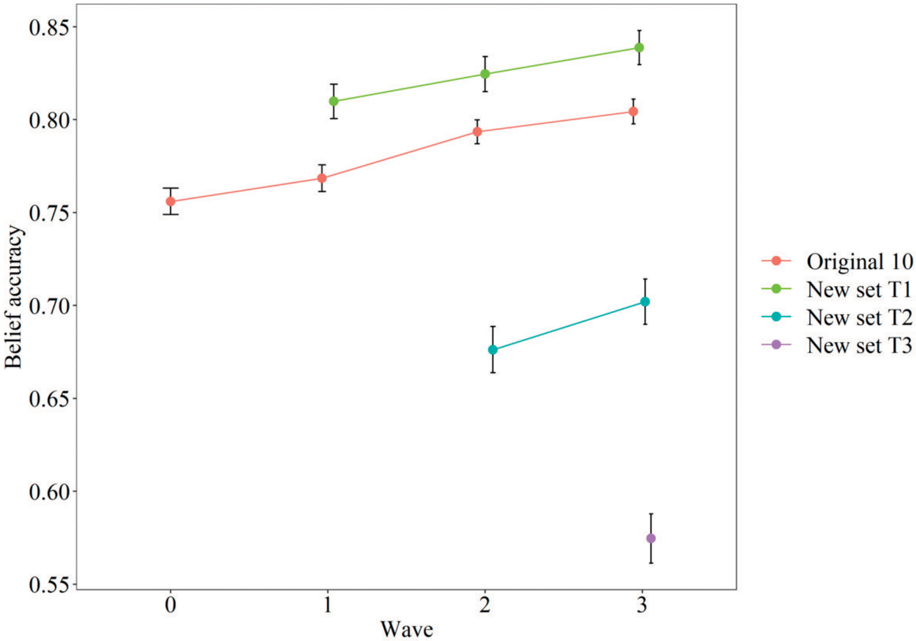
Note. Due to rounding, percentages may not add up to 100% exactly. The percentages in census data reflect the population aged 18 years and over.

Belief Accuracy

Mean scores of belief accuracy were very high at all waves, with scores reflecting low belief in false statements and high belief in true statements. There was substantial variation in the accuracy of responses between statements, although none of the statements was ever interpreted with less than 0.25 accuracy on average (see Appendix H for a complete overview of scores per statement per wave).

There was a modest increase in belief accuracy over time, looking at each set of statements separately (first 10: estimate=0.02, se<0.01; $t_{3202.59}$=13.82, *P*<.001; T1 set: estimate=0.01, se<0.01; $t_{2041.94}$=4.80, *P*<.001; T2 set: estimate=0.02, se<0.01; $t_{1003.22}$=3.40, *P*<.001). This increase was positive for all three sets of statements that were asked more than once (see Figure 2), indicating that participants became more accurate in their interpretation of the statements over time.

Figure 2 Belief Accuracy per Set of Statements over Time



Note. The new set at T3 was included for completeness. Focusing on within subject change, dots represent normed means, error bars indicate 95% confidence intervals (CI) of the within-subject standard error (Morey, 2008), calculated using the summarySEwithin function from the Rmisc package (Hope, 2016).

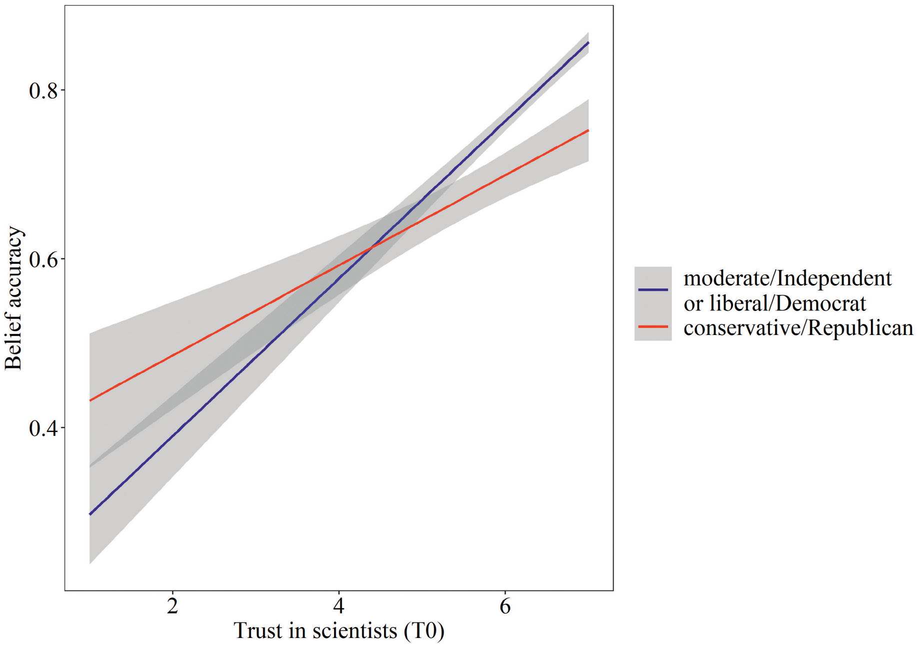
Coronavirus-related Behavior

Accurate beliefs were correlated with self-reported behavior aimed at preventing the coronavirus from spreading (*r* at all waves between 0.26 and 0.29, all *P*s<.001). This small, but robust correlation suggests that accurate beliefs could be important for coronavirus-related behavior. We explored potential evidence of any causal effects in the data using a random intercept cross-lagged panel model (RI-CLPM). This yielded a tentative indication that accurate beliefs might be predictive of behavior, with belief accuracy at T2 predicting coronavirus-related behavior at T3. However, with all other paths showing no sign of significant predictive effects, the results regarding causality are largely inconclusive (see Appendix I).

Associations with Belief Accuracy

We explored the relationship of trust in scientists (at T0), political orientation, and the primary news source with belief accuracy. The mixed model yielded a significant positive relation between belief accuracy and trust (estimate=0.07, se<0.01; $t_{1200.23}$=16.44, P<.001), and a significant negative correlation with political orientation (estimate=-0.02, se<0.01; $t_{1199.62}$=-6.78, P<.001). These main effects indicated that participants with higher trust in scientists scored higher on the measure of belief accuracy and that liberal/Democratic participants held more accurate beliefs than conservative/Republican participants. Moreover, these main effects were partially qualified by an interaction effect among trust and political orientation (estimate=-0.01, se<0.01; $t_{1195.05}$=-3.62, P<.001). Plotting of this interaction effect demonstrated that trust in scientists had a stronger relationship with belief accuracy for liberal/Democratic participants than it had for conservative/Republican participants (see Figure 3).

Figure 3 Linear Relationship Between Belief Accuracy by Trust in Scientists at T0, Split by Political Orientation

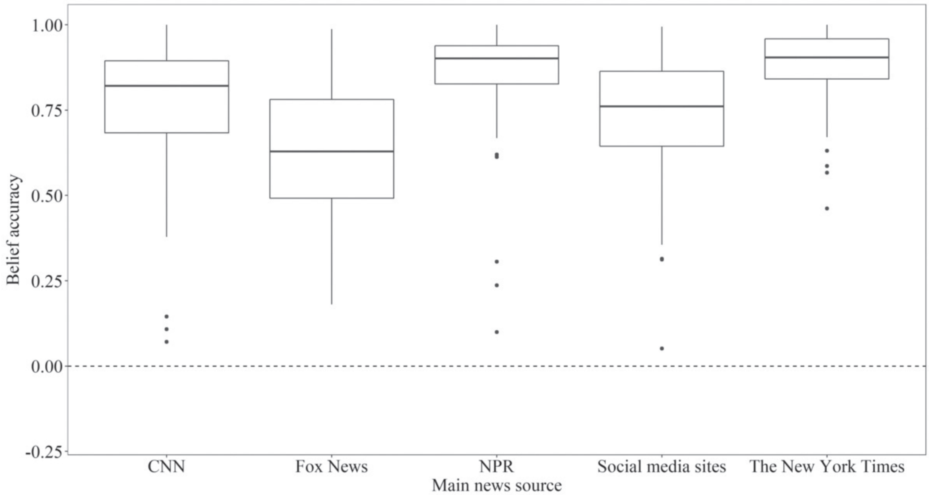


Note. Linear relationship between belief accuracy (averaged over wave for plotting) by trust in scientists at T0, split by political orientation (dichotomized for plotting). The grey area represents the 95% CI.

Two of the five most chosen primary news sources were associated with a worse understanding of the facts regarding the COVID-19 pandemic than others (see Figure 4). Participants who reported CNN (estimate=-0.03, se=0.01; $t_{1194.49}$=-2.33, P=.02) or Fox

News (estimate=-0.05, se=0.02; $t_{1202.49}$=-3.05, *P*=.002) as their main news source scored below average on belief accuracy.

Figure 4 Boxplot of Belief Accuracy by Main News Source



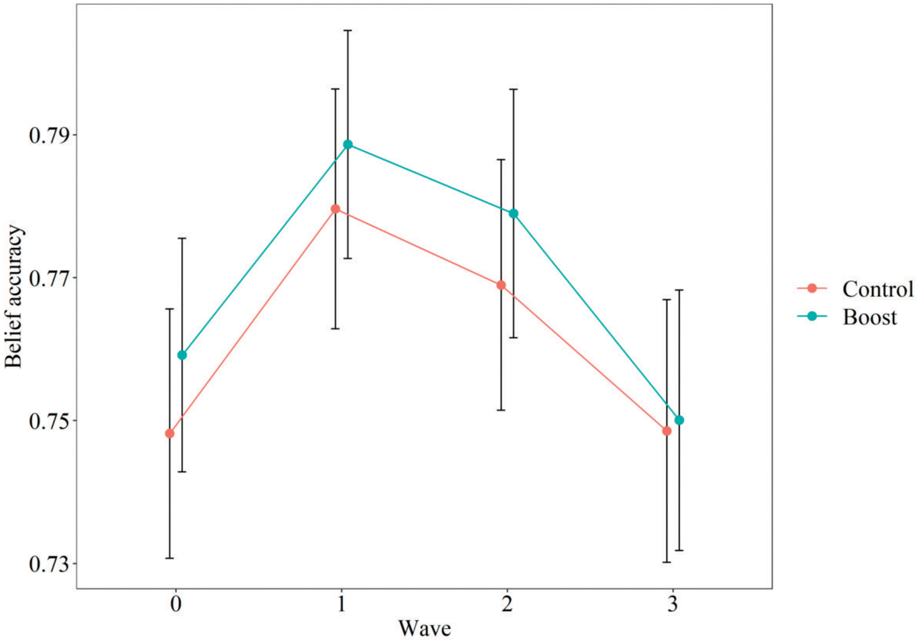
Note. Belief accuracy was averaged over wave for plotting.

Intervention

We conducted a manipulation check and, as expected, when asked how they evaluated claims, participants in the boost condition mentioned consensus (or something similar) more often (136 out of 600; 22.7%) than participants in the control condition (26 out of 602; 4.3%; χ^2(1, N=1202)=85.18, *P*<.001).

We hypothesized that our boosting intervention would lead to more accurate beliefs about the COVID-19 pandemic than control. However, the interaction effect between condition and wave on belief accuracy was not significant (estimate<0.01, se<0.01; $t_{1074.36}$=0.22, *P*=.83). This means that the boosting intervention did not significantly alter belief accuracy of participants over time, compared to control (see Figure 5). This was also the case when we explored effects of the intervention on inaccurate statements only (*P*=.48), accurate statements only (*P*=.49), only the original 10 statements that were included in all waves (*P*=.61), and only included participants who scored relatively low on belief accuracy at T0 (belief accuracy$_{T0}$<0.76; *P*=.32).

Figure 5 Belief Accuracy per Condition over Time

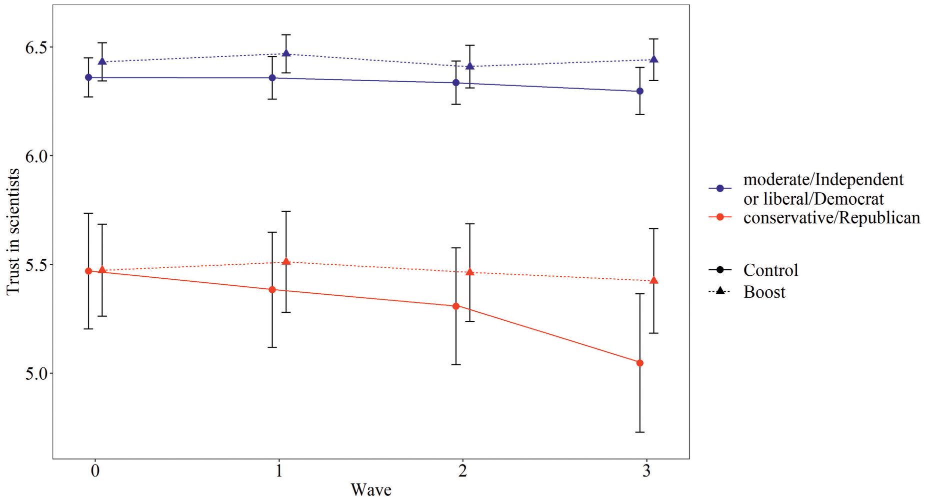


Note. Error bars indicate 95% CI focusing on the comparison between experimental conditions, not adjusted for within-subject variability.

When comparing the subsample of participants in the boost condition that mentioned consensus (or similar) in the manipulation check to participants in the control condition, we again found that the intervention did not increase belief accuracy (*P*=.21). However, there was a main effect of condition (estimate=0.06, se=0.02; $t_{725.66}$=3.50, *P*=.001), indicating that participants in the boost condition who did use consensus while evaluating claims scored higher on belief accuracy than participants in the control condition. This difference was already present at baseline, so was not caused by the intervention.

We explored the effect of the boosting intervention on trust in scientists as a source of information about the coronavirus. The mixed effects model, similar to the hypothesis test but with the repeated measure of trust as the dependent variable and including the interaction term between condition, wave, and political orientation, yielded a significant three-way interaction effect between condition, wave, and political orientation (estimate=0.02, se=0.01; $t_{1088.42}$=2.39, *P*=.02). Trust in scientists was very high in all four waves (means between 6.11 and 6.19), but investigation of the two-way interaction effects per condition indicated a significant interaction effect among wave and political orientation in the control condition (estimate=-0.02, se=0.01; $t_{562.01}$=-3.24, *P*=.001), while there was no such significant interaction effect in the boost condition (*P*=0.90). As illustrated by Figure 6, there was a clear overall difference in trust in scientists between participants related to their political orientation. More interestingly, trust remained stable for all participants in the boost condition, but decreased slightly for conservative/Republican participants in the control condition. This could indicate that the boosting intervention inhibited a decline of trust in scientists as a source of information about the coronavirus among more conservative/Republican participants.

Figure 6 Trust in Scientists as a Source of Information per Condition and Political Orientation over Time



Note. Political orientation was dichotomized for plotting. Error bars indicate 95% CI focusing on the comparison between experimental conditions, not adjusted for within-subject variability.

Discussion

Principal Results

The aims of this study were to gain insight into the beliefs of the US public about the COVID-19 pandemic and to investigate whether a boosting intervention could improve people's belief accuracy. Interestingly, the average scores on belief accuracy over the surveyed four-week period were high, indicating low belief in false statements and high belief in true statements. Looking at each set of statements, we found a small but significant increase in belief accuracy over time. This indicates that the general public is quite able to figure out what is true and what is not in times of crisis. Moreover, a small, but robust correlation suggests that accurate beliefs about the pandemic might be important for coronavirus-related behavior. Associations with belief accuracy suggest that the processes of belief formation and correction might be affected by individuals' trust in scientists and political orientation, as well as their news habits. Finally, the boosting intervention yielded no significant increase in belief accuracy over control, demonstrating that the boosting infographic was not successful in helping people figure out what is true and what is false. Exploratory analyses suggested that the intervention did, however, inhibit a decline in trust in scientists as a source of information about the coronavirus among more conservative/Republican participants.

Comparison with Prior Work

There is a great deal of worry about the prevalence of misinformation in the current pandemic, which is reflected in popular media (e.g., Gallagher & Bell, 2020; O'Sullivan, 2020), as well as among scientists (e.g., Mian & Khan, 2020; Van Bavel et al., 2020) and public health agencies (e.g., NHS England, 2020; World Health Organization, 2020). The supposed COVID-19 infodemic is not reflected in US citizens' beliefs. The finding that most Americans hold quite accurate beliefs about the COVID-19 pandemic is in line with emerging work on perceptions of the pandemic that shows that belief in COVID-19 misperceptions and conspiracy theories is quite low (Ballew et al., 2020; Pennycook, McPhetres, Bago, et al., 2020; Roozenbeek et al., 2020; Sutton & Douglas, 2020). Consequently, this calls into question the prevalence of misinformation or the public's susceptibility to misinformation.

A convincing body of empirical work on the prevalence of misinformation surrounding the COVID-19 pandemic is not yet available. Research from before the COVID-19 pandemic indicates that the prevalence of misinformation might be lower than many believe (Allen et al., 2020; Fletcher et al., 2018; Guess, Nyhan, et al., 2020). Still, it is possible that the current pandemic has led to an increase in misinformation compared to the information landscape from before the pandemic. However, when looking for potential explanations of the current findings, we should consider the possibility that COVID-19 misinformation is not as prevalent as expected. Perhaps misinformation makes up only a small portion of the average US citizen's media diet?

The second possibility is that we are indeed facing a COVID-19 infodemic, but that the public is not very susceptible to it. Misinformation campaigns regarding other topics, such as climate change and the health effects of tobacco (Cook, 2016; Oreskes & Conway, 2011), have demonstrated that misinformation can contribute to misperceptions about important matters. In these cases however, misinformation campaigns have been carefully organized and executed, continually misinforming the public for decades. In contrast, the COVID-19 pandemic is a novel issue and, at least in the relatively early months that we investigated, did not yield many such coordinated misinformation campaigns. Moreover, the COVID-19 pandemic originated in a very different media landscape than the climate and tobacco misinformation campaigns. Fake news, misinformation, and disinformation have been discussed widely and frequently in popular media since the 2016 US presidential election and the 2016 United Kingdom European Union membership referendum. This might have resulted in the public being more aware of campaigns targeted at misinforming them. Perhaps the widespread discussion of misinformation in popular media has worked as a large scale media literacy intervention, putting people ‘on guard’ against false information. In support of this idea, recent research has demonstrated that simply asking one to consider the accuracy of a claim improved subsequent choices about what COVID-19 news to share on social media (Pennycook, McPhetres, Zhang, et al., 2020).

A third possibility that should be considered is that the public is more careful in forming beliefs in times of crisis, especially in the relatively early days of a crisis, making a well-informed public not unique to the COVID-19 pandemic. In times of crisis, people are likely to increase news consumption (Westlund & Ghersetti, 2015). This was also the case in the US during the first months of the COVID-19 pandemic, with people reporting increased news consumption (Global Web Index, 2020). Though we find that those who reported CNN or Fox News as their main news source scored below average on belief accuracy, the general increase in news consumption may lead to a better understanding of the crisis situation, including more accurate beliefs.

Turning to the finding that political orientation is associated with individuals' belief accuracy, we see that this is in line with other emerging work (Pennycook, McPhetres, Bago, et al., 2020). There is likely a multitude of explanations for this evolving partisan divide (Funk & Tyson, 2020) on perceptions about the pandemic, such as political party cues in the news affecting opinion formation (Leeper & Slothuus, 2014), the difficulty of correcting false beliefs for the ideological group most likely to hold those misperceptions (Nyhan & Reifler, 2010), as well as the differences in news consumption that are reflected in this study. A second variable that is even more strongly related to belief accuracy is trust in scientists as a source of information about the coronavirus, demonstrating that higher trust is related to more accurate beliefs. Interestingly, the associations of political orientation and trust with accurate beliefs were partially explained by an interaction effect among political orientation and trust. The stronger association of trust with belief accuracy for more liberal/Democratic individuals might mean that they rely more on scientists' perceptions in forming beliefs, while relatively more conservative/Republican individuals might rely more on other cues. Relatedly, the inhibited decline in trust in scientists among conservative/Republican participants in the boost condition could indicate that information about the scientific process might resonate more with them than just hearing the results of this process. Though this exploratory finding should be replicated, it could provide a fruitful avenue for further research on trust in scientists and political orientation.

In addition, this study demonstrates that some news sources might be doing a worse job of informing their consumers about the COVID-19 pandemic than others, or perhaps that better informed news consumers turn to different news sources than less well-informed consumers (again in line with other emerging work; Pennycook, McPhetres, Bago, et al., 2020). Most likely, a combination of both selection and influence (e.g., Slater, 2015) explain the differences in belief accuracy found in this study. Interestingly, considering the role of social media in the spread of misinformation (e.g., Goodier, 2020), with about 26-42% of tweets in the data collection period containing unreliable facts (Gallotti et al., 2020), participants who reported social media sites as their main source of news about the coronavirus did not display significantly worse belief accuracy than others. However, it is possible that participants who reported social media sites as their main source followed major news outlets via the social media site, thereby being exposed to similar news content as the other participants.

Finally, this study demonstrates the difficulty of crafting interventions aimed at increasing belief accuracy. Recent work demonstrates that simple, short media literacy interventions can work (Guess, Lerner, et al., 2020; Hameleers, 2020), while other work highlights the difficulties of crafting these interventions (Vraga et al., 2020). We argue that the divergent findings can be explained by the fact that in the former work the interventions were paired with corrections, while in this study participants had to put their new skill to use outside of the study context. Considering that cues signaling the existence of consensus in relevant news content are very rare (Merkley, 2020), participants likely had to search for information about scientific consensus themselves. The results from the manipulation check indicated that only a relatively small portion of participants actually applied this strategy. However, those individuals that indicated that they did apply a strategy related to consensus reasoning scored higher on belief accuracy than control. This difference highlights the potential of the intervention in situations where individuals can be empowered to actually apply it.

Limitations

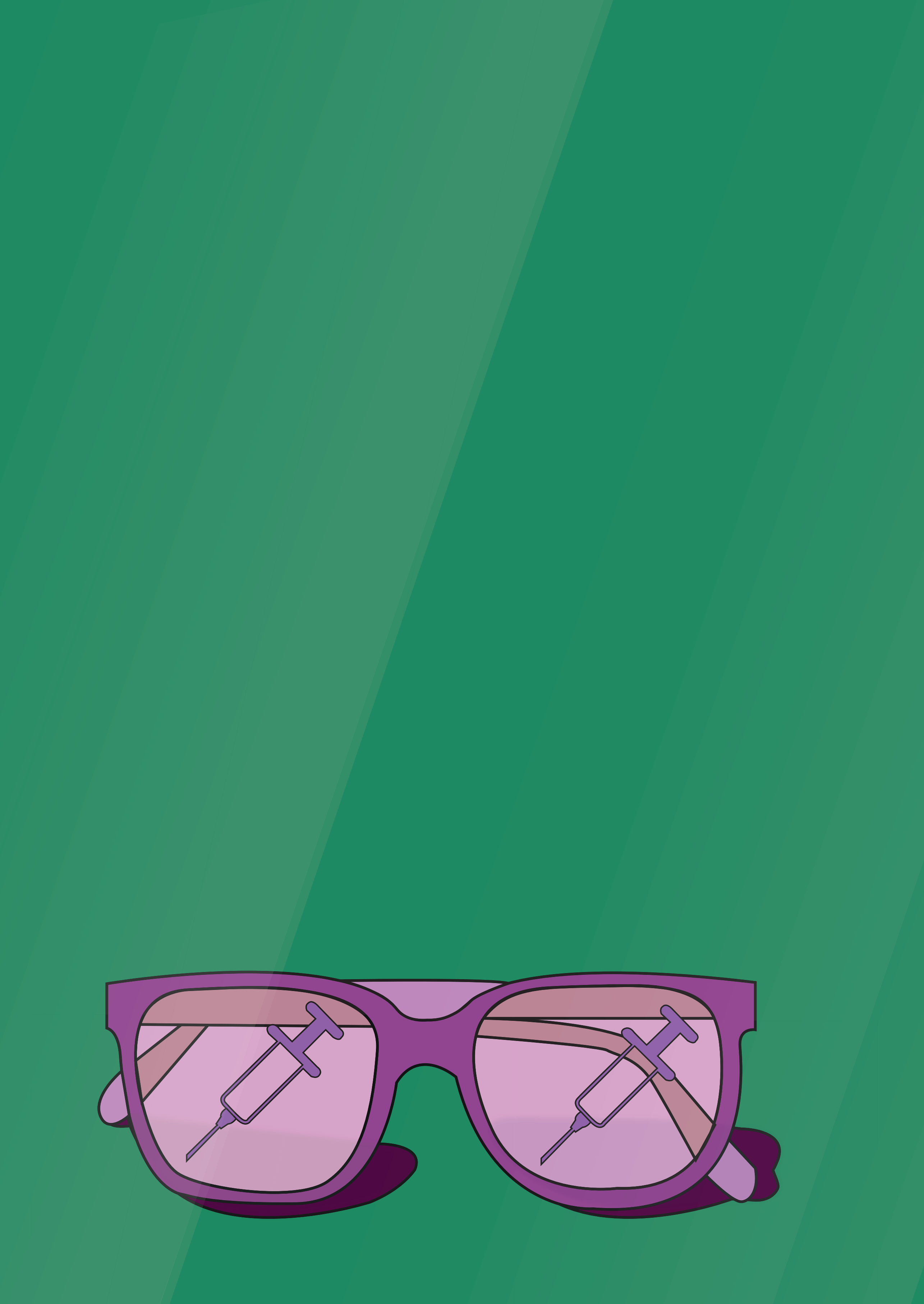
There are two notable limitations to this study. First, our belief accuracy measure consisted only of science-based statements. We incorporated only science-based claims in our study to ensure that there was sufficient, empirical evidence either stating a claim was true or false. However, this decision did exclude some coronavirus-related claims that were not based on science (e.g., “Bill Gates patented the coronavirus”) or unresolved at the time (e.g., “A vaccine will be available before the end of the year”). It should have been harder for participants to figure out whether such unresolved issues were true or not, yielding different responses from participants for a measure reflecting non-science based, unresolved issues about the pandemic.

A second limitation is the fact that the recruitment platform that we used, Prolific, is known as a platform for research. Although participants on the platform receive financial incentives for completing studies, they might be more interested in scientific research than the average US citizen. This could lead to them also having a higher trust in science than the general population, even though our sample was balanced on age, gender, and ethnicity. As trust in science was highly related to belief accuracy, it could be possible that this led to an inflated belief accuracy score. Future research should attempt to replicate this study with a sample that represents the US population better than our balanced sample.

Conclusions

Our work demonstrates that most people are quite able to figure out the facts in this time of crisis, but also that it is difficult to intervene on these beliefs. However, in cases where people do not immediately have a clear understanding of the facts, they are capable of figuring them out over time. There are some factors that might make it easier or harder for one to figure out the facts. We found that the accuracy of participants' beliefs was related to political orientation, as well as the primary news source. This suggests that, even in the relatively early days of the pandemic, political polarization and media diet had a grip on US citizens' factual beliefs, leading to polarization along party lines. Another factor strongly related to accurate beliefs about the pandemic was trust in scientists. It is unclear whether an already high trust led to accurate beliefs or that being able to figure out the facts increased trust in scientists, but the importance of expert communication is underlined by these findings.

Although a small but robust correlation suggests that accurate beliefs about the pandemic might be important for coronavirus-related behavior, the role of misinformation in the pandemic seems to be relatively small, either because it is rare or because it is unable to persuade. However, we note that even if misinformation is not prevalent and only accepted by a small portion of the receivers, it can still be dangerous. To illustrate, we found that almost all participants in this study disregarded the statement that injecting or ingesting bleach is a safe way to kill the coronavirus, but this false claim is reported to have cost at least one life (Shorman & Chambers, 2020). Additionally, with the anti-vaccine community launching coordinated misinformation campaigns against potential coronavirus vaccines (Burki, 2020) and politicization of the pandemic looming, the infodemic might become a much bigger threat.



Miscellaneous

Appendices

References

Data Management and Transparency

Dutch Summary

Acknowledgements

About the Author

Appendices

Appendix A: Motivation manipulation from Chapter 2

Directional condition
"You will now read a short text about [vaccines and the immune system / E numbers].

We are interested in your judgment, because you believe that [multiple vaccines can overload a young child's immune system / food additives indicated with E numbers are unsafe to consume]. While reading the text, please try to be aware of this belief and view the information from your perspective. For instance, try to think of what information could confirm your initial belief.

So please
- be aware of your belief
- apply your perspective
- think of what would confirm your initial belief"

Accuracy condition
"You will now read a short text about [vaccines and the immune system / E numbers].

We are interested in your judgment, because we study how people process information and come to conclusions. While reading the text, please try to view the information in an even-handed way and from various perspectives. For instance, try to think of what information could disprove your initial belief.
So please
- be even-handed
- apply various perspectives
- think of what would disprove your initial belief"

Default condition (Experiment 2 only):
"You will now read a short text about E numbers.

Please read it like you normally would."

Appendix B: Corrective messages from Chapter 2

Experiment 1

The following text is based on material that was published by the NHS and Science, one of the world's top scientific journals.

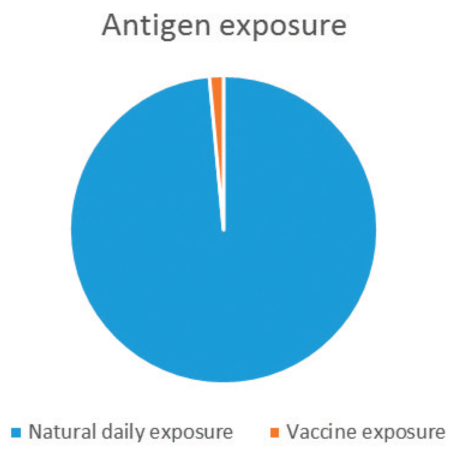
Vaccines won't overload your child's immune system

Some parents are concerned that giving too many vaccines at the same time will "overload" a child's immune system, especially at 1 year of age, when four injections are given in a single session. But this isn't the case. Over and over, studies have shown there are no harmful effects from giving multiple injections or vaccines in one session.

Now, a new study provides even further evidence for this. Researchers examined the medical records of more than 900 infants from six hospitals and clinics across the western United States between 2003 and 2013. The team compared children who had contracted diseases not covered by vaccinations with those who didn't. There was no link between vaccines given before the age of 2 and other infections from ages 2 to 4. This indicates that, looking at any disease other than what is vaccinated against, children who receive the vaccine are not more likely to become ill than children who did not receive the vaccine.

The results aren't surprising. First of all, this is in line with the scientific consensus. Years of research have demonstrated that vaccines cannot overload a child's immune system. Second, we know why the immune system can handle a vaccine. As soon as a baby is born they come into contact with a huge number of different bacteria and viruses every day, having gone from a sterile womb straight into to our bacteria-filled environment. Their immune system copes with them and becomes stronger as a result. The immune system challenge from bacteria and viruses in vaccines pales in comparison. The bacteria and viruses used in vaccines are weakened or killed, and there are far fewer of them than the natural bugs that babies and children come into contact with (see figure below).

Immunisation helps to improve protection against life-threatening diseases at the very earliest opportunity.



According to the University of Oxford Vaccine Knowledge Project vaccines for babies and children contained just over 60 antigens (molecules capable of eliciting an immune response) in total, in 2012. According to the American Academy of Pediatrics the amount of antigens that children fight every day ranges from 2,000 to 6,000.

Experiment 2

The following text is based on material that was published by the Food Standards Agency (FSA) and scientific research published in the academic journal Food Quality and Preference.

Food additives indicated with E numbers are safe to consume

Some consumers are concerned that food additives that are indicated with an E number are dangerous chemicals that are not safe to consume. But this isn't the case. All the foods we eat consist of chemicals in one form or another. An E number just indicates that a food additive has passed safety tests and is approved for use in the UK and in the EU as a whole.

Food additives have a long history of consumption and are used in many traditional foods. For example, wines including Champagne contain sulphites and bacon contains the preservatives nitrates and nitrites to prevent the growth of harmful bacteria, such as those that cause potentially fatal diseases like botulism. Many food additives are chemicals which exist in nature such as antioxidants ascorbic acid (vitamin C) or citric acid, found in citrus fruits. Even oxygen can be used as an additive (E number 948). Due to technological advancements, many additives are now man-made to perform certain technological functions, such as preventing food from spoiling. Whether or not the chemicals used in additives exist in nature, they are subject to the same safety evaluations by the FSA.

The safety of food additives is tested in scientific studies investigating acute toxicity, short-term exposure at various doses, and life-time exposure over several generations. If not generally considered safe, a maximum dose is set for use in specific foods: the acceptable daily intake (ADI). This is the dose that can be safely consumed daily over a lifetime without causing an effect in humans. Only when all the safety tests are passed, does the additive get the E number (for all rules, see graphic below). Even when an E number is assigned, the additive gets re-evaluated regularly to investigate whether it is safe, based on the latest scientific research.

The E numbers on labels on food products are meant as a reassurance, to indicate that the ingredients have been tested and found safe.

When is a substance an E number?

Assigning an E number to a substance follows these rules.

1

Manufacturer must prove necessity of use.

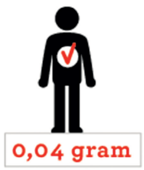
2

Limit to lowest dose to accomplish desired effect.

3

Safety tests.

4



Determine acceptable daily intake (ADI).

5

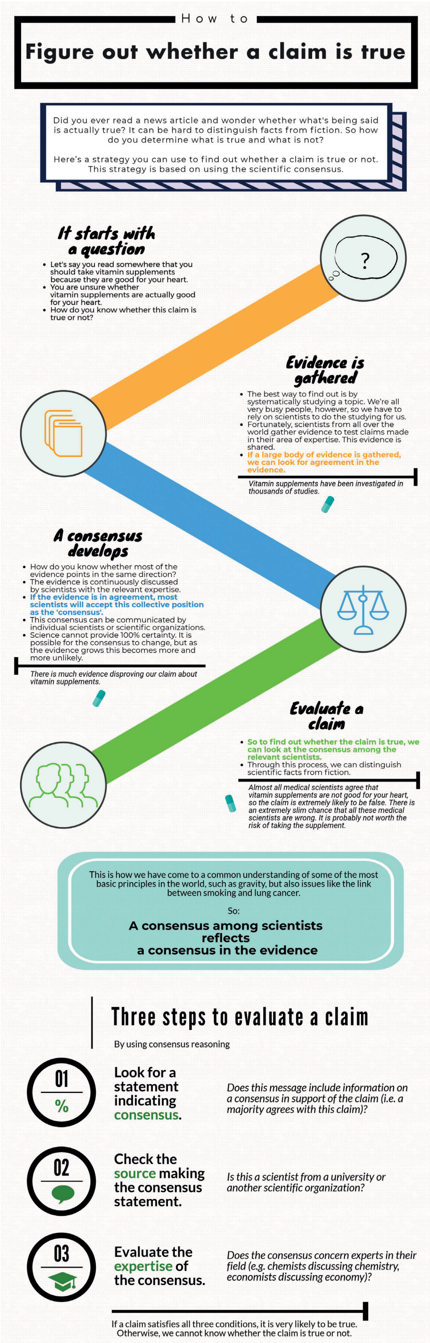
E number gets leaflet for manufacturer that states to which products which dose can be added.

6

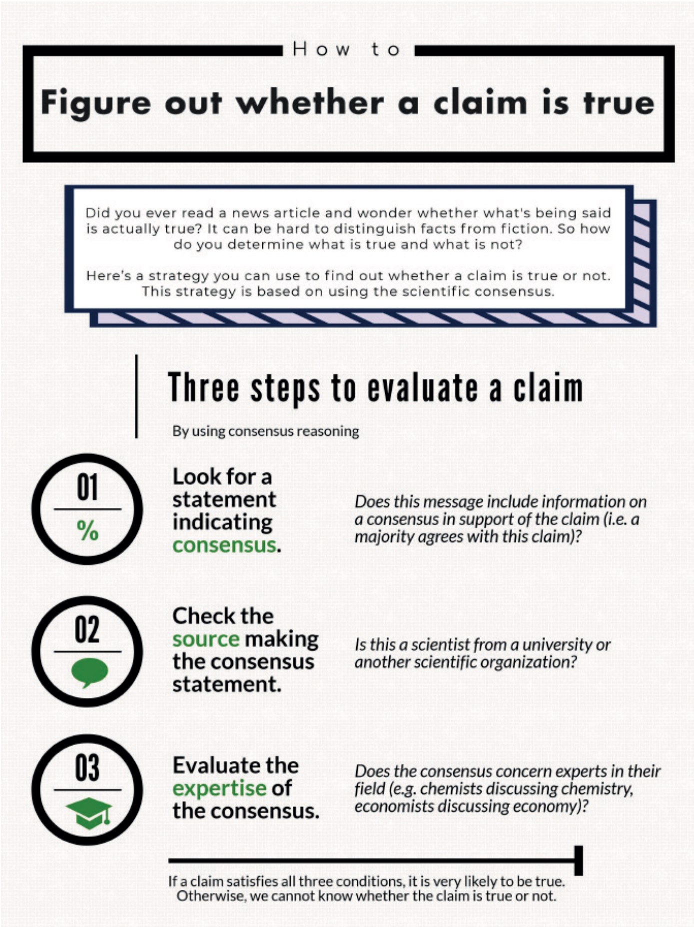
Based on actual intake from all food sources determine that ADI is not exceeded.

Appendix C: Consensus reasoning manipulation from Chapter 4

Appended Figure 1 Infographic Used in Boost+ Condition



Appended Figure 2 Infographic Used in Boost Condition



Appended Figure 3 Infographic Used in Consensus-only and Control Condition

Appendix D: Prior and posterior belief and perceived consensus scores from Chapter 4

Appended Table 1 Prior and Posterior Belief and Perceived Consensus Means (and SDs) per Experiment by Condition.

Experiment	Variable	Condition									
		Boost+		Boost		Consensus- only		Control		**Mean**	
		Prior	Post	Prior	Post	Prior	Post	Prior	Post	**Prior**	**Post**
Experiment 1	Belief in human-caused climate change	-57.93 (28.26)	-44.00 (44.96)	-65.80 (29.13)	-48.26 (51.22)	-60.04 (27.70)	-47.28 (45.87)	-	-	**-61.33 (28.45)**	**-46.55 (47.31)**
	Perceived climate consensus	60.08 (25.04)	79.54 (24.16)	55.82 (25.98)	75.64 (26.76)	56.04 (24.53)	73.97 (26.24)	-	-	**57.27 (25.16)**	**76.35 (25.75)**
Experiment 2	Belief in GE misperception	60.24 (28.67)	9.44 (58.56)	61.01 (29.25)	20.17 (57.25)	58.05 (28.35)	20.51 (53.57)	-	-	**59.78 (28.72)**	**16.71 (56.62)**
	Perceived GE food consensus	47.80 (24.73)	78.89 (22.71)	45.43 (23.93)	72.97 (25.85)	45.90 (23.46)	71.05 (26.75)	-	-	**46.37 (24.02)**	**74.3 (25.33)**
Experiment 3	Belief in GE misperception	57.65 (28.03)	2.62 (58.59)	-	-	56.32 (28.32)	18.93 (51.80)	56.49 (28.73)	30.91 (43.66)	**56.81 (28.34)**	**17.78 (52.78)**
	Perceived GE food consensus	45.36 (24.00)	74.45 (25.82)	-	-	45.98 (24.11)	71.20 (25.67)	42.65 (23.80)	51.52 (25.50)	**44.64 (23.99)**	**65.52 (27.58)**

Note. Scores calculated before model outliers were removed.

Appendix E: Attention and seriousness checks from Chapter 5

An attention check was included in the measure of belief accuracy in all waves. Attention checks are used to filter out careless responding, which has been demonstrated to improve the quality of survey data (Meade & Craig, 2012). The attention check consisted of an instructed-response item, which stated "To demonstrate that you are paying attention, please answer "False". Furthermore, at T0, a seriousness check was included. Seriousness checks are also used to improve data quality (Aust et al., 2013). The seriousness check consisted of telling participants that as researchers, the quality of their data was very important to us, so we wanted to make sure that their responses were valid and authentic. We asked them "In your honest opinion, should we use your data?" Participants responded with either "Yes" or "No".

Appendix F: Resources used to collect COVID-19 pandemic belief statements for Chapter 5

Empirical research:

- Preprint by Pennycook et al. (2020)
- Preprint by Singh et al. (2020)

Media tracking organizations:

- RCAID COVID-19 Insights Center: https://covid19.rcaid.org/
- NewsGuard: https://www.newsguardtech.com/covid-19-myths/

Expert reports in established media:

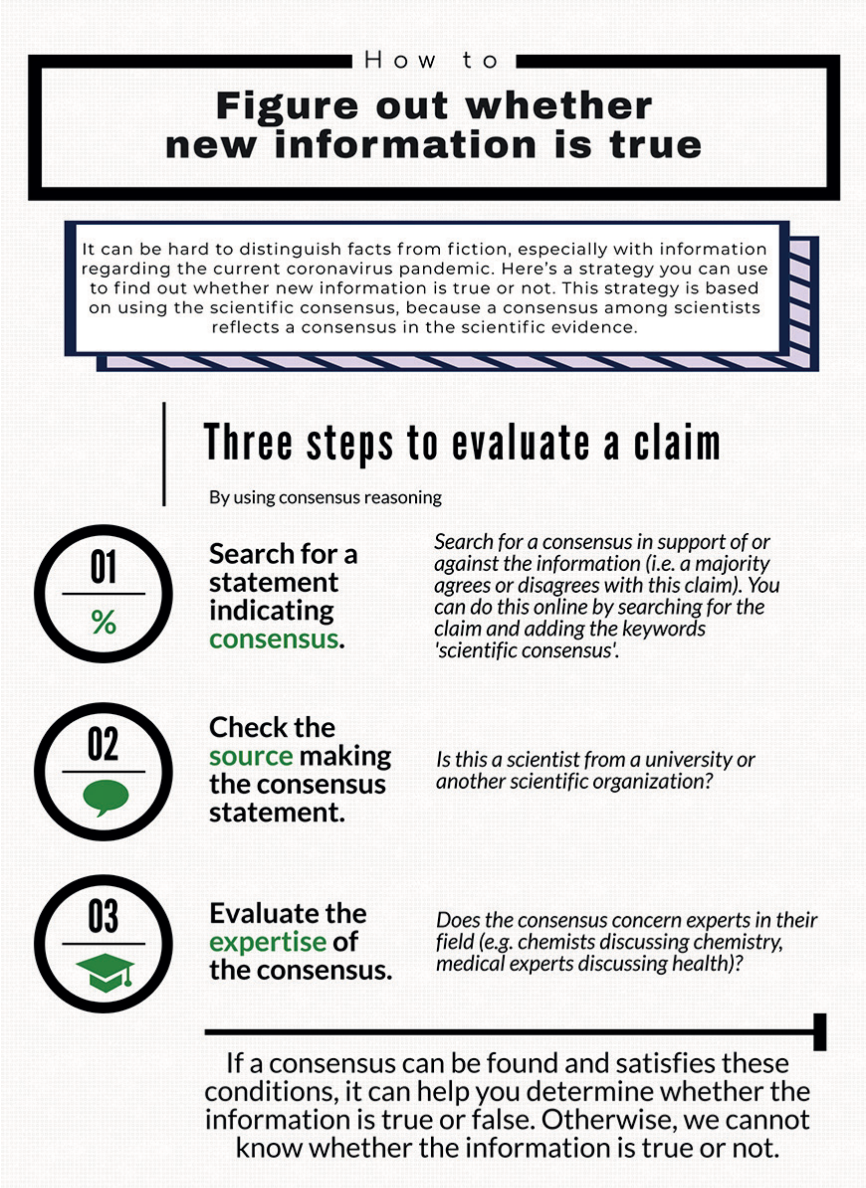
- BBC Reality Check: https://www.bbc.com/news/reality_check
- CNBC Expert Debunking: https://www.cnbc.com/2020/05/01/experts-explain-why-coronavirus-myths-misinformation-can-be-dangerous.html
- The Guardian: What do scientists know: https://www.theguardian.com/world/2020/apr/30/coronavirus-what-do-scientists-know-about-covid-19-so-far
- The Guardian: Coronavirus myths busted: https://www.theguardian.com/world/2020/apr/11/can-a-face-mask-protect-me-from-coronavirus-covid-19-myths-busted

Public health agencies and medical institutes:

- WHO myth busters: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/myth-busters
- Harvard Medical School Coronavirus Resource Center: https://www.health.harvard.edu/diseases-and-conditions/coronavirus-resource-center

Appendix G: Intervention material from Chapter 5

Appended Figure 4 Infographic Used in the Boosting Intervention to Empower Participants to Use the Scientific Consensus When Evaluating Claims Related to the COVID-19 Pandemic



Appendix H: Descriptive statistics of all statements per wave from Chapter 5

Appended Table 2 Mean Belief Accuracy (and SD) per Belief Statement per Wave

Statement	Wave			
	Wave 0 (N=1202)	Wave 1 (n=1078)	Wave 2 (n=1067)	Wave 3 (n=1022)
Radiation from 5G cell towers is helping spread the coronavirus	0.85 (0.35)	0.86 (0.34)	0.86 (0.33)	0.87 (0.33)
The coronavirus is man-made	0.52 (0.55)	0.52 (0.55)	0.56 (0.54)	0.57 (0.54)
Complementary products, such as colloidal silver or herbal remedies, have been proven effective in preventing or treating COVID-19	0.73 (0.44)	0.74 (0.44)	0.76 (0.44)	0.77 (0.43)
The coronavirus is a biological weapon developed by the Chinese government	0.60 (0.51)	0.62 (0.50)	0.64 (0.49)	0.64 (0.50)
A safe and effective vaccine for COVID-19 is available at this time	0.90 (0.32)	0.89 (0.32)	0.89 (0.31)	0.88 (0.34)
The name given to the novel 2019 coronavirus is Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2)	0.28 (0.72)	0.42 (0.72)	0.54 (0.65)	0.62 (0.62)
Regular hand washing can help prevent the spread of the coronavirus	0.92 (0.22)	0.93 (0.21)	0.92 (0.22)	0.93 (0.23)
Fever is one of the symptoms of COVID-19	0.91 (0.25)	0.91 (0.30)	0.92 (0.25)	0.92 (0.26)
The elderly are at a higher risk of becoming severely ill due to COVID-19	0.92 (0.24)	0.93 (0.23)	0.93 (0.25)	0.93 (0.24)
Social distancing helps slow the spread of the coronavirus	0.91 (0.26)	0.91 (0.26)	0.91 (0.26)	0.90 (0.28)
Injecting or digesting bleach is a safe way to kill the coronavirus	–	0.97 (0.19)	0.96 (0.21)	0.97 (0.19)
Warm weather stops the coronavirus from spreading entirely	–	0.61 (0.51)	0.62 (0.51)	0.64 (0.51)
The coronavirus spreads mainly from person-to-person	–	0.83 (0.33)	0.84 (0.32)	0.88 (0.28)
There is a delay between the moment a person is first infected with the coronavirus and the time this person develops symptoms	–	0.84 (0.34)	0.87 (0.30)	0.87 (0.32)
The vast majority of people who contract the coronavirus will need to be hospitalized	–	–	0.58 (0.58)	0.60 (0.58)
There is overwhelming evidence for the safety and effectiveness of hydroxychloroquine in treating COVID-19	–	–	0.58 (0.57)	0.63 (0.56)

Appended Table 2 Continued

Statement	Wave			
	Wave 0 (N=1202)	Wave 1 (n=1078)	Wave 2 (n=1067)	Wave 3 (n=1022)
Some people who have been infected with the coronavirus have no symptoms	–	–	0.88 (0.34)	0.90 (0.30)
COVID-19 is more deadly than the seasonal flu	–	–	0.66 (0.54)	0.67 (0.54)
Pets are a source of infection with the coronavirus by spreading the virus to humans	–	–	–	0.51 (0.55)
There is strong evidence that vitamin C can cure COVID-19	–	–	–	0.76 (0.42)
The coronavirus originated in wildlife	–	–	–	0.32 (0.60)
Currently there is no specific effective antiviral treatment for COVID-19	–	–	–	0.70 (0.51)

Appendix I: Random intercept cross-lagged panel model (RI-CLPM) from Chapter 5

We used a RI-CLPM to explore the relationship between the accuracy of participants' coronavirus and COVID-19 beliefs and their reported coronavirus-related behavior. RI-CLPMs are an analytical strategy used to describe directional influences between variables over time, focusing on the within-person variation (Hamaker et al., 2015). We fit a model in which the means of each variable were unconstrained over time, including the variance and covariance over time. The fit measures indicated good model fit (RMSEA=0.021, SRMR=0.012, CFI=0.999). Only one of the cross-lagged paths was statistically significant, indicating that belief accuracy at T2 might be predictive of coronavirus-related behavior at T3 (see Appended Table 3). Note that the autoregressive path of coronavirus-related behavior at T2 was still significant as well.

Appended Table 3 Regression Paths in RI-CLPM Exploring the Relationship Between Belief Accuracy and Coronavirus-related Behavior

Outcome	Predictors	Estimate	SE	*Z*	*P*
BA T3	BA T2	0.50	0.07	6.94	<.001
	CB T2	-0.01	0.02	-0.63	.53
BA T2	BA T1	0.04	0.15	0.26	.79
	CB T1	0.03	0.03	1.04	.30
BA T1	BA T0	0.00	0.07	0.04	.96
	CB T0	-0.03	0.03	-1.00	.32
CB T3	CB T2	0.39	0.09	4.16	<.001
	BA T2	0.74	0.30	2.44	.015
CB T2	CB T1	0.13	0.13	0.97	.33
	BA T1	-0.14	0.56	-0.26	.80
CB T1	CB T0	-0.23	0.22	-1.05	.29
	BA T0	0.02	0.25	0.10	.92

Note. BA = belief accuracy, CB = coronavirus-related behavior.

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Research Data Management and Transparency

The Radboud University and the Behavioural Science Institute (BSI) have set conditions for the management of research data. The research data presented in this dissertation are treated in accordance with both the Radboud University and BSI research data management protocols. A complete research data management protocol specific to the research presented in this dissertation has been uploaded to the Radboud Information System (RIS). In addition, all anonymized data and R scripts used in the analyses are publicly available in the Open Science Framework (OSF; www.osf.io/uwzky).

Dutch Summary

We zijn het niet allemaal eens over de feiten met betrekking tot een aantal belangrijke uitdagingen waar we voor staan. Mispercepties, feitelijke overtuigingen die onjuist zijn of in tegenspraak zijn met het beste beschikbare bewijs in het publieke domein, dragen bij aan het voortdurende bestaan van belangrijke problemen zoals klimaatverandering, ondervoeding en besmettelijke ziekten. Wetenschapscommunicatie speelt een belangrijke rol in het informeren van het publiek over deze onderwerpen, maar een substantieel aantal wetenschapscommunicatoren en onderzoekers vraagt zich af of het simpelweg communiceren van de wetenschap nog wel werkt om het publiek te informeren over de feiten. Hoe kan dat? En kunnen feiten zo gecommuniceerd worden dat ze het publiek wel informeren? Deze vragen staan centraal in dit proefschrift; het doel was om te onderzoeken hoe mensen vasthouden aan onjuiste overtuigingen terwijl ze geconfronteerd worden met accurate informatie en hoe wetenschapscommunicatie verbeterd kan worden om mensen te helpen tot wetenschappelijk accurate overtuigingen te komen.

Op basis van verschillende experimenten, een meta-analyse en een longitudinale studie komen we dichter bij antwoorden op deze vragen. Ten eerste, de studies laten zien dat mensen soms, ondanks blootstelling aan accurate informatie, vasthouden aan mispercepties omdat ze daartoe gemotiveerd zijn. Ons onderzoek toont dat redeneren over corrigerende informatie met als doel tot een specifieke conclusie te komen ertoe kan leiden dat iemand minder geneigd is een overtuiging aan te passen dan redeneren met accuraatheid als doel. Ten tweede, met betrekking tot de vraag hoe wetenschap beter gecommuniceerd kan worden, tonen de bevindingen aan dat wetenschapscommunicatie verbeterd kan worden door gebruik te maken van de waarde van wetenschappelijke consensus (overeenstemming onder wetenschappers). Zulke boodschappen zijn effectief in het informeren van het publiek, alhoewel dit effect nog uitgebreider getest moet worden buiten gecontroleerde experimentele settings en op de lange termijn. Daarnaast kan hulp bij het identificeren en begrijpen van wetenschappelijke consensus bijdragen aan het verder verminderen van mispercepties, in ieder geval als het gaat om onjuiste overtuigingen over genetisch gemanipuleerd voedsel.

Onze bevindingen staan in schril contrast met enkele van de veelvoorkomende ideeën in het veld, dat tot voor kort vooral stelde dat corrigerende informatie waarschijnlijk averechts zou werken en mispercepties zou versterken. Dit proefschrift biedt juist ruimte voor optimisme: veel mensen staan open voor wetenschappelijke informatie. Alleen het geven van accurate informatie zal waarschijnlijk niet altijd effectief zijn om mensen te informeren, maar het zou vaker kunnen werken dan een lezing van de academische literatuur of artikelen uit populaire media doen verwachten.

Acknowledgements

About the Author

I obtained my bachelor's degree in communication science at Radboud University in Nijmegen. Subsequently, I obtained a research master's degree in behavioral science at the Behavioural Science Institute at the same university. After graduating, I spent one year at Utrecht University as a Junior Researcher to investigate the effect of situational cues on food preference and consumption. Looking to set up my own research on science communication, I returned to the Behavioural Science Institute to start a PhD project, which has led to the work you are holding right now.

Currently, I am a post-doctoral researcher at the Behavioural Science Institute, where I continue to study science communication. For a current overview of my work, please visit www.aartvanstekelenburg.com.

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