Title: Communicating expert consensus increases personal support for COVID-19 mitigation policies

Short title: *Communicating consensus on COVID-19*

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Abstract:

The Gateway Belief Model (GBM) places perception of a scientific consensus as a key “gateway cognition” with cascading effects on personal beliefs, concern, and ultimately support for public policies. However, few studies seeking to evaluate and extend the model have followed the specification and design of the GBM as originally outlined by van der Linden et al. (2015). We present a more complete test of the theoretical model in a novel domain: the COVID-19 pandemic. In a large multi-country correlational study (N = 7,206) we report that, as hypothesized by the model, perceptions of scientific consensus regarding the threat of COVID-19 predict personal attitudes toward threat and worry over the virus, which are in turn positively associated with support for mitigation policies. We also find causal support for the model in a large pre-registered survey experiment (N = 1,856): experimentally-induced increases in perceived consensus have an indirect effect on changes in policy support mediated via changes in personal agreement with the consensus. Implications for the role of expert consensus in science communication are discussed.

Keywords:

Gateway Belief Model, Scientific Consensus, COVID-19.

Data availability statement:

Data and analysis code are available at: https://osf.io/gk9uv/?view_only=a508b50750074b1ab178c92984c2ed3e

Conflict of interest statement:

The authors have no conflicts of interest to declare.

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On the 30th of January 2020, the World Health Organization declared the growing COVID-19 outbreak a Public Health Emergency of International Concern (WHO, 2020). Preventing and slowing the spread of the virus, which at the time of writing has claimed more than 3.2 million lives, has become a priority for policy-makers around the globe (Hale et al., 2020; WHO, 2021). In recent reviews, social and behavioral scientists have highlighted the critical role of research in (a) informing efforts to communicate evidence regarding the virus (Blastland et al., 2020), (b) counter misinformation (van der Linden et al., 2020), and (c) encourage both support for policies and the adoption of preventative behaviors (Van Bavel et al., 2020). These efforts are critical for an effective response to pandemics in terms of promoting health protecting actions directly (e.g., social distancing, vaccination), but also in combatting misinformation and misperceptions which may lead people to reject such actions. This can ultimately lead to the prevention of deaths from COVID-19, as well as expediting a return to economic and social normalcy (Flaxman et al., 2020; Lytras & Tsiodras, 2020). Among the strategies outlined by Van Bavel et al. (2020), the communication of scientific norms was noted as one approach to shifting beliefs and behavior, drawing on the credibility of the scientific community (see also, Rutjens et al., 2021). Although this remains untested in the context of the COVID-19 outbreak, there is a growing body of evidence that communication of scientific agreement can shift personal beliefs, and policy support, across a range of scientific domains. This notion is captured by the Gateway Belief Model (GBM).

The Gateway Belief Model

The GBM (van der Linden et al., 2019; van der Linden, Leiserowitz, et al., 2015) is a dual-process theory of attitude change that posits a two-stage mediational process where perceptions of scientific consensus act as a key 'gateway cognition' to influencing personal agreement with scientific claims which in turn predict support for related policies. The GBM has been applied to a diverse set of contested issues, including genetically modified (GM) organisms (Dixon, 2016; Kerr & Wilson, 2018; Kobayashi, 2021), vaccination (van der Linden, Clarke, et al., 2015), Brexit (Harris et al., 2019), vitamin supplements (Kobayashi, 2018), and climate change (Bolsen & Druckman, 2018; van der Linden et al., 2019; van der Linden, Leiserowitz, et al., 2015). Such studies have formed the basis of communication campaigns (Goldberg, van der Linden, Ballew, et al., 2019) and offer greater insights into how perceptions of expert agreement inform individuals' beliefs about a wide range socially relevant and publicly debated issues.

The GBM builds on theory derived from established dual-process models of persuasion such as the Elaboration Likelihood Model and Heuristic-Systematic model (van der Linden, 2021). Within such models, heuristics—rules of thumb—are applied as mental shortcuts to reduce cognitive effort. Two particular heuristics are especially relevant in the context of the GBM: sources which are deemed more credible are more persuasive (the credibility heuristic; *experts can be trusted*) as are claims which a supported by a majority of the group (the consensus heuristic; *consensus implies correctness*). The impact of consensus information (e.g., "97% of experts think that X") is considered in the light of social influence research, with scientific consensus representing "informational influence" (Deutsch & Gerard, 1955) or a descriptive social norm (Cialdini, 2007) within a broadly trusted group of experts (Funk et al., 2020; van der Linden, 2021). As noted by Cialdini and colleagues, "audiences are powerfully influenced by the combined judgment of multiple experts" (Cialdini et al., 2015, p. 23). As a heuristic, this makes good sense, people often favor expert over regular crowds when forming judgments under uncertainty, which helps people tap collective wisdom fast and efficiently (Mannes et al., 2014).

Scientific consensus cues can also spread in social networks via interpersonal discussion with friends and family (Goldberg, van der Linden, Maibach, et al., 2019). This is important because just as people often misperceive social consensus, for example, around binge drinking (Prentice & Miller, 1993) and polarization (Van Boven et al., 2018), so too do people misperceive the scientific consensus on a range of issues, from climate change to vaccination (Pew, 2015). Correcting people's perception of the norm often leads to subsequent (smaller) changes in private attitudes and behavior (Tankard & Paluck, 2016). Targeting second-order normative beliefs (i.e., beliefs about what other people believe) has revealed potential in changing first-order beliefs (i.e. personal beliefs; Goldberg, van der Linden, Maibach, et al., 2019; Mildenberger & Tingley, 2019). The GBM leverages norm perception as a vehicle for change in a similar manner: revealing the consensus among experts can be a powerful strategy to align people's perception of the norm with the actual scientific norm resulting in positive downstream consequences on private attitudes and policy support (Lewandowsky et al., 2012; van der Linden et al., 2019; van der Linden, Leiserowitz, et al., 2015).

In the original GBM, van der Linden et al. (2015) outline two possible mediators of the effect of consensus perceptions on policy support: worry, capturing an affective component; and personal belief or agreement, representing a cognitive pathway. Although the GBM has been applied in a range of domains, most deviate from van der Linden et al.'s (2015) original model. For example, many tests of the GBM in different contexts have only examined the role of perceived consensus as a mediator of the effect of a message on personal agreement with the consensus claim (Dixon et al., 2015; Kerr & Wilson, 2018). Fewer studies have examined policy support as an outcome and those that do tend to focus only on personal agreement as a mediator, i.e. they do not include worry as a further path by which perceived consensus can affect policy attitudes (e.g. Bolsen & Druckman, 2018). This omission is not trivial, as the GBM posits that both cognitive (personal agreement with consensus position) and affective (worry) elements mediate the effect of perceived consensus on policy support. In other words, how concerned people are and how much they worry about an issue explains additional variance, over and above awareness of a problem, in predicting support for mitigation policies across a range of domains (Goldberg, Gustafson, et al., 2020; Huang & Yang, 2018; Salvaggio et al., 2014).

Accordingly, a recent review has called for more comprehensive and direct confirmatory tests of the GBM (van der Linden, 2021). The pandemic presents a large scale, socially relevant phenomenon of much concern to the general public (Dryhurst et al., 2020) and is the focus of a number of publicly-debated policies which aim to mitigate its impact (Balmford et al., 2020). Yet, little is currently known about the general public's perceptions of scientific agreement regarding the overall threat of COVID-19 and how this relates to their personal beliefs and attitudes about the pandemic. This is especially relevant in light of current debates about the politicization of science (Druckman, 2017) and whether exposure to evidence can cause belief polarization (Kahan et al., 2011; Kobayashi, 2018; van der Linden, Leiserowitz, & Maibach, 2017). These studies will therefore provide novel insights into how expert agreement shapes public attitudes toward the coronavirus and policies aimed at mitigating its spread.

Current studies

In Study 1 we apply the GBM to beliefs about the threat posed by the coronavirus during the initial stages of the outbreak (March-May, 2020), as the scientific community worked to build a greater understanding of the virus and its potential impacts. This timing is important as it offers insight into how perception of expert consensus relates to personal belief and policy support regarding a novel, but highly salient scientific issue. This is in contrast to many of the prior issues to which the GBM has been applied that have been the subject of scientific research and public debate for decades (e.g., climate change, GM food, and vaccination). We ask: does perception of a scientific consensus predict personal agreement that COVID is a public health emergency, and worry over the virus? And do these constructs subsequently predict support for policies intended to curtail its spread?

There are number of ways we could operationalize perceptions of scientific consensus and personal agreement regarding the threat posed by the COVID-19 pandemic. In the current studies we opted to use the wording of the WHO, which declared COVID-19 to be a "Public Health Emergency of International Concern" (PHEIC) in January 2020 (WHO, 2020). This technical definition captures an overall perception of the virus as a threat and aligns with the actual language used by the scientific community in the lead up to WHO declaration (Science Media Centre, 2020). This approach also aligns with previous work on the GBM in the context of climate change in that the focal claim is *descriptive*, that is, it does not convey agreement about *what should be done*, only that there is agreement on the existence of a challenge to be addressed (e.g. climate change; van der Linden et al., 2019).

In Study 1 we present a test of the GBM using cross-sectional data. Following from the GBM, we hypothesize that perceptions of scientific consensus regarding the threat posed by COVID-19 will be associated with personal agreement with the consensus position and worry over COVID-19. We also hypothesize that, perceptions of scientific consensus will have a positive, indirect effect on support for policies intended to mitigate the spread of the virus mediated via personal agreement and worry.

In Study 2 we undertake a pre-registered experimental test of the causal paths assumed in the Study 1 model. We compare the effects of a high (97%) or low (60%) consensus message outlining the level of scientific agreement regarding COVID-19's designation as a PHEIC. Following from van der Linden et al.'s (2019) specification of the GBM, we expect that high and low consensus messages will respectively increase or decrease perceived scientific consensus and that these shifts will in turn predict subsequent, smaller changes in personal agreement and worry, which in turn predict changes in policy support. Specifically, we hypothesize that shifts in perceived consensus will have an indirect effect on changes in policy support, mediated via shifts in personal agreement and worry.

Study 1

Methods

Participants

Data for this study were collected as part of a larger series of surveys investigating a range of COVID-related attitudes and risk perceptions (see Dryhurst et al., 2020; Roozenbeek et al., 2020). We recruited participants in several countries taking different approaches to managing the pandemic: UK, US, Spain, Mexico, and Ireland. We note that at the time of data collection, all countries had in place some form of 'stay at home' mandate (Hale et al., 2021). Participants were primarily recruited through an International Organization for Standardization (ISO) certified online panel provider (Respondi; respondi.com), using interlocking national quotas to ensure final samples were matched to population in terms of age and gender. Surveys in the UK were conducted at two time points and two additional national UK samples were recruited through Prolific (prolific.co), with screening quotas for age, gender, and ethnicity to approximately match the UK population (Prolific, n.d.). For each recruitment platform, UK participants who completed a survey were excluded from participating in subsequent surveys[1]. The survey dates, size and demographic profile of each sample are shown in Table 1.

Sample size was determined by resources available in the context of the larger COVID-19 research program. While our primary focus is the pooled sample, all individual samples still exceed the sample size outlined by Fritz and MacKinnon (2007) as adequate to detect a mediated effect in which both *a* and *b* paths are 'small' (by Cohen's standards of effect size; equivalent to β = .14) at .8 power in analyses employing BCa bootstrap intervals as the test of the mediated effect (N = 462).

Table 1. Sample details

Country	Participant platform	Date (2020)	N	Women (%)	M_{age} (SD)	Tertiary educated (%)
Total	-	-	7206	51.05	44.71 (15.79)	54.18
Spain	Respondi	May-06	700	50.43	46.00 (15.03)	56.71
Ireland	Respondi	Apr-24	700	50.00	45.85 (16.32)	53.00
Mexico	Respondi	May-06	700	51.00	38.61 (14.21)	75.57
UK	Prolific	Apr-09	1049	50.62	45.16 (15.63)	56.82
UK	Prolific	May-07	1157	50.73	44.72 (15.66)	56.53
UK	Respondi	Apr-09	1050	52.00	45.39 (16.00)	42.29
UK	Respondi	May-07	1150	52.00	45.72 (15.94)	43.39
US	Respondi	May-07	700	51.00	45.03 (16.08)	59.14

Participants completed the survey on the Qualtrics platform and were paid £1.00-£2.79. All participants provided informed consent and the study was overseen by the Psychology Research Ethics Committee at the University of Cambridge.

Materials

Participants completed items capturing their perception of scientific agreement on COVID-19 being a PHEIC ("What percentage of medical scientists do you think agree that coronavirus/COVID-19 is a Public Health Emergency of International Concern?" Sliding scale, 0-100%), their own personal agreement with this claim ("The COVID-19 virus is a Public Health Emergency of International Concern"; Strongly disagree (1) to strongly agree (5)), their level of worry over COVID-19 ("*How worried are you personally about the following issues at present? - Coronavirus/COVID-19*"; Not at all worried (1) to Very worried (7)) and support for a Work from Home policy ("*I support a government policy requiring all non-essential workers to stay at home*"; Not at all (1) to Very much (7)). This particular policy was selected as it was presented as a key response to control the spread of the virus (Acuña-Zegarra et al., 2020; Cairney, 2021; Henríquez et al., 2020), was relevant across national contexts, and supported by evidence at the time of data collection as an effective strategy to reduce non-household contacts and control the spread of the virus (Ferguson et al., 2020). Where required, survey instruments were translated by a native Spanish speaker fluent in English.

Participants in the US, UK, and Ireland samples also answered an additional policy item relevant to the local context at the time: "*I believe the current lockdown should continue for at least another 3 weeks*". This policy item reflected UK government signalling at the time of initial data collection (Hughes, 2020) and was deemed relevant for the US and Ireland, where authorities had extended lockdown restrictions (BBC, 2020; Quinn, 2020). Results for this measure as a dependent outcome were comparable (see Supplementary Information, Appendix 2).

Results

In all countries, the mean perceived level of scientific consensus regarding the severity COVID-19 was high (M_{pooled} = 86.21%, SD = 16.35; individual country *M*s = 82.58-90.42%). Mean levels of personal agreement (M_{pooled} = 4.57, SD = 0.81; *M*s = 4.39-4.74), worry (M_{pooled} = 5.85, SD = 1.38; *M*s = 5.58-6.11) and support for working from home (M_{pooled} = 5.77 SD = 1.59; *M*s = 4.89-6.39) were also high, with values above the scale mid-point across all samples (descriptive results and zero-order correlations are reported in Supplementary Information, Table S1). We report results for the entire pooled sample here but note that the pattern of effects was similar across all samples. We draw attention to descriptive differences between countries where appropriate.

To empirically test the fit of the GBM in relation to COVID-19 attitudes, we constructed a serial mediation model using the *R* package lavaan (Rosseel, 2012) outlined in

Figure 1. This approach allows estimation of indirect effects via multiple sequential mediators as well as combined indirect effects (Hayes, 2017). Perceived consensus is positioned as an exogenous variable predicting personal agreement and worry, which in turn predicts policy support. As per the original GBM (van der Linden, Leiserowitz, et al., 2015), we also include a path by which personal agreement predicts worry. Analyses employed a MLR estimator (robust fit measures reported).

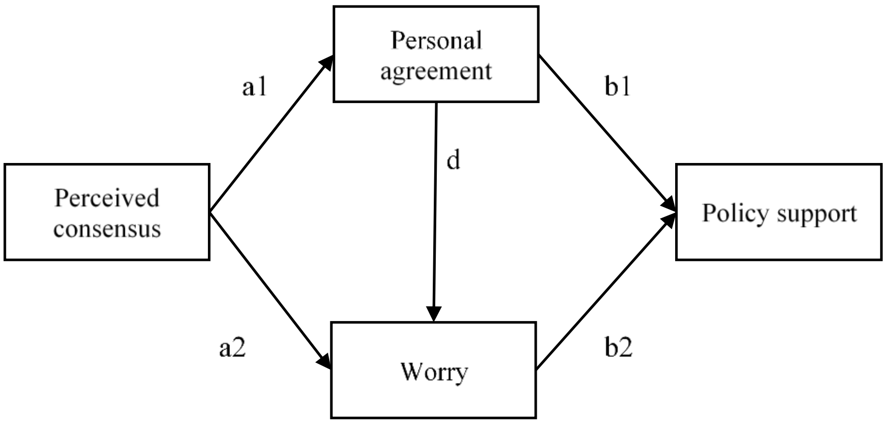

Figure 1. Diagram of GBM model in relation to COVID-19 attitudes.

The model fit the pooled data from all samples well ($X^2(1) = 424.06$, $p < .001$; CFI = .967; SRMR = .039; RMSEA = .168, 95CI [.154, .181]) and we also report good fit for the model in each individual sample (CFIs = .942-.997; SRMRs = .014-.049; RMSEAs = .067-.215; see Supplementary Information Table S2). We note that the RMSEA value is above the commonly accepted criterion of .06 (Hu & Bentler, 1999). As noted by Kenny et al. (2015), this is typical of models with low degrees of freedom. Kenny and colleagues recommend in such cases that a fully saturated model is used to estimate regression coefficients. Thus, in Table 2 we report the regression coefficients for each path in the saturated model, i.e. the paths outlined in Figure 1 and the direct effect of consensus on policy support (*c*).

As shown in Table 2, in the pooled sample we report a significant, positive effect of perceived consensus on personal agreement, indicating that individuals who perceive greater scientific agreement on the threat of COVID-19 express greater personal agreement that pandemic is a public health emergency. Higher perceived consensus is also associated with worry over COVID-19, as is personal agreement. In turn both agreement and worry are associated with greater support for a work from home policy.

We report a significant overall combined indirect (i.e. mediated) effect of consensus on policy support (β = 0.20, unstandardized b = 0.02, 95CI [0.02, 0.02]; bootstrapped (5000 samples; bias corrected accelerated) confidence intervals do not include zero. This represents the sum of effects of consensus mediated by three different paths (outlined in Figure 1): via agreement, via worry, and via agreement then worry.

Table 2. COVID-19 GBM path coefficients, indirect and total effect in pooled sample

Path	Label	β	b	95CI
Consensus → Agreement	a1	0.50***	0.02	[0.02, 0.03]
Consensus → Worry	a2	0.19***	0.02	[0.01, 0.02]
Agreement → Worry	d	0.38***	0.66	[0.62, 0.70]
Agreement → WFH	b1	0.29***	0.57	[0.53, 0.61]
Worry → WFH	b2	0.15***	0.18	[0.16, 0.19]
Consensus → WFH	c	0.17***	0.02	[0.02, 0.02]
Combined indirect effect		0.20***	0.02	[0.02, 0.02]
Total effect		0.37***	0.04	[0.03, 0.04]

Note: WFH = Support for work from home policy. ***p <.001

Similarly, when the model is fitted to data from each individual sample we find a significant indirect effect of perceived scientific consensus on policy support, mediated via personal agreement and worry (βs 0.08 - 0.41; Table 3, full results reported in Supplementary Information, Table S3). While the patten of effects is consistent with the pooled samples, we do note that the pooled results mask some differences between countries in terms of the magnitude of effects in the model. For example, the smallest indirect (and total) effect of perceived consensus on policy support was reported in the Spanish sample ($\beta_{indirect}$ = 0.08) and the largest in the US sample ($\beta_{indirect}$ = 0.41) with all other samples in the range of βs 0.14-0.21.

Table 3. Combined indirect and total effects of perceived consensus on policy support in individual samples.

Sample	Indirect effect			Total effect		
	β	*b*	95CI	β	*b*	95CI
Spain	0.08	0.01	[0.00, 0.02]	0.28	0.03	[0.03, 0.04]
Ireland	0.14	0.01	[0.01, 0.01]	0.35	0.03	[0.02, 0.03]
Mexico	0.16	0.02	[0.01, 0.02]	0.31	0.03	[0.03, 0.04]
UK (Prolific; Apr)	0.19	0.02	[0.01, 0.02]	0.31	0.03	[0.02, 0.04]
UK (Prolific; May)	0.21	0.02	[0.02, 0.03]	0.31	0.03	[0.03, 0.04]
UK (Respondi; Apr)	0.22	0.02	[0.01, 0.02]	0.44	0.04	[0.03, 0.04]
UK (Respondi; May)	0.21	0.02	[0.01, 0.02]	0.40	0.03	[0.03, 0.04]
US	0.41	0.04	[0.03, 0.05]	0.49	0.05	[0.04, 0.05]

Note: Indirect effect is the combined effect of consensus on policy support mediated via agreement and worry (i.e. three separate paths; see Figure 1). All effects are significant (i.e., 95% confidence intervals do not include zero).

Interim discussion

Study 1 reveals that, across eight high-powered international samples, our primary hypothesis is supported: the perception of scientific consensus on COVID-19 predicts support for relevant policies and these effects are mediated by worry over COVID-19 and personal belief that the pandemic represents a public health emergency. We do note some between-country variability in the magnitude of the hypothesized indirect effect. Descriptive comparison of indirect effects across samples indicates that perceived consensus is a stronger predictor of policy support in the US compared to other countries, with the smallest effect reported in Spain. Given the myriad differences between countries—both in terms of culture and pandemic response—it is difficult to pinpoint moderating factors. However, possible explanations for further investigation include country-level differences in deference to scientists regarding policy (Post et al., 2021) or variation in perceptions of the efficacy of government measures (Mækelæ et al., 2020). Purely as an example, it is possible that Spanish participants were more skeptical of the efficacy of a work from home policy and thus worry and perceived threat were not as strongly associated with support for this measure. While the current study took advantage of multi-country data collection, it was not designed to identify country-level moderators. Further cross-cultural work is therefore needed to examine how effects in the GBM vary across different countries.

We must also acknowledge that the conclusions drawn from these results are necessarily limited by study's correlational nature; we cannot make any strong claims about the causal direction of these effects. In Study 2 we investigate the causal direction of effects by experimentally manipulating perceptions of consensus.

Study 2

As a causal test of the GBM, we conducted a consensus messaging experiment following the design of van der Linden et al. (2019). In brief, we sought to confirm that experimentally-induced changes in perceived consensus lead to changes in policy support, with these effects mediated by changes in worry over COVID-19 and belief that the pandemic is an international emergency. Study 1 focused on government-mandated working from home as a policy support variable. In Study 2, we measure policy support using an index of support for a wider range of specific policies that were in place in the UK at the time of data collection. We also report an additional exploratory analysis investigating the moderating role of political ideology in the GBM, as interaction effects have been reported in the climate change domain (van der Linden et al., 2019). The study was pre-registered (https://aspredicted.org/blind.php?x=sh7se2).

Methods

Participants

Adult UK residents were recruited in September 2020 via Respondi and Prolific using interlocking quotas to ensure national samples matched to the UK population in terms of age and gender (and ethnicity in the case of Prolific; see Prolific, n.d). All participants provided informed consent and were paid £1.25-£2.05. The study was overseen by the Psychology Research Ethics Committee at the University of Cambridge. A total of 1,856 participants took part in the experiment (938 via Prolific, 918 via Respondi; 51.7% female, M_{age} = 42.0, SD = 16.0; median education level: school education up to age 18; 81.8% white ethnicity). As per our pre-registration, 127 participants (6.8%) who failed an attention check ("*To make sure you are paying attention, please select 'Agree' for this statement"*) were removed.

Like Study 1, the current experiment was embedded in a larger survey and thus the sample size was dictated by considerations other than statistical power for the analyses presented here. However, using Fritz and MacKinnon's (2007) simulation study as a guide, the sample size is larger than that required to detect a mediated effect in which both *a* and *b* paths are 'small' (by Cohen's standards of effect size; equivalent to $\beta = .14$) at .8 power in analyses employing BCa bootstrap intervals as the test of the mediated effect ($N = 462$).

Procedure

Participants completed the survey experiment on the Qualtrics platform. Participants were randomly assigned to one of three experimental conditions: control ($n = 573$), low ($n =$

583), and high (n = 573) consensus. Following van der Linden et al., (2015), participants first completed all pre-test measures before being asked to read a message reportedly drawn from a database of media statements. In the high [low] message condition this statement read: *Did you know? An estimated 97% [60%] of medical scientists agree that the COVID-19 outbreak is a Public Health Emergency of International Concern*. In the control condition participants read an unrelated consensus statement: *Did you know? An estimated 97% of dentists agree that that regular toothbrushing prevents tooth decay and cavities* (see Goldberg, van der Linden, Ballew, et al., 2019). Following the manipulation, participants completed a filler block of items asking where they had seen information about COVID-19 (e.g. news media, social media) before completing all post-test items.

Materials

Participants completed the following items before and after the experimental manipulation: perception of scientific agreement on COVID-19 being a PHEIC, their own agreement with this claim and their level of worry over COVID-19 (item wording identical to Study 1). Participants also reported their support for four separate policies relating to COVID-19 restrictions which were already in place in the UK at the time of data collection (Government of the United Kingdom, 2020) and aimed to reduce the introduction and transmission of the virus: *nationwide lockdown in the event of a widespread second wave of infections*; *mandatory mask use on public transport and in indoor public spaces*; *mandatory 2-week self-quarantine for travelers returning or arriving from countries with increasing infection rates*; and, *banning private gatherings of more than 6 people (except in certain instances such as weddings*) (all *strongly oppose* (1) to *strongly support* (7)). Policy support was indexed as the average of these four items (pre-test α = .84; post-test α = .85).

Following the experiment, participants also reported their political ideology (1 = very liberal/left wing to 7 = very conservative/rightwing; M = 3.59, SD = 1.38), and were recoded into three groups: left-wing (responding 1-3; n = 772), moderate (4; n = 555) and right-wing (5-7; n = 398). Four participants with missing data for this item were excluded from relevant analyses.

Results

Means and standard deviations for each variable before and after the experimental manipulation, and the difference between them, are shown in Table 4 and Figure 2.

Table 4. Mean responses pre and post manipulation and mean individual-level change.

Variable	Experiment condition	Pre		Post		Post-pre	
		M	*SD*	*M*	*SD*	*M*	*SD*
Consensus	Low	80.43	18.62	67.32	14.99	-13.10	17.41
	Control	82.11	17.40	82.52	17.47	0.45	6.11
	High	83.11	16.33	91.51	12.87	8.39	12.58
Agreement	Low	6.19	1.23	6.16	1.22	-0.04	0.76
	Control	6.29	1.10	6.27	1.18	-0.02	0.72
	High	6.30	1.09	6.41	1.02	0.11	0.67
Worry	Low	5.29	1.73	5.33	1.76	0.04	0.70
	Control	5.36	1.67	5.44	1.69	0.08	0.67
	High	5.39	1.58	5.50	1.59	0.10	0.58
Policy support	Low	5.72	1.38	5.76	1.41	0.04	0.37
	Control	5.73	1.31	5.75	1.36	0.02	0.40
	High	5.80	1.24	5.84	1.23	0.04	0.37

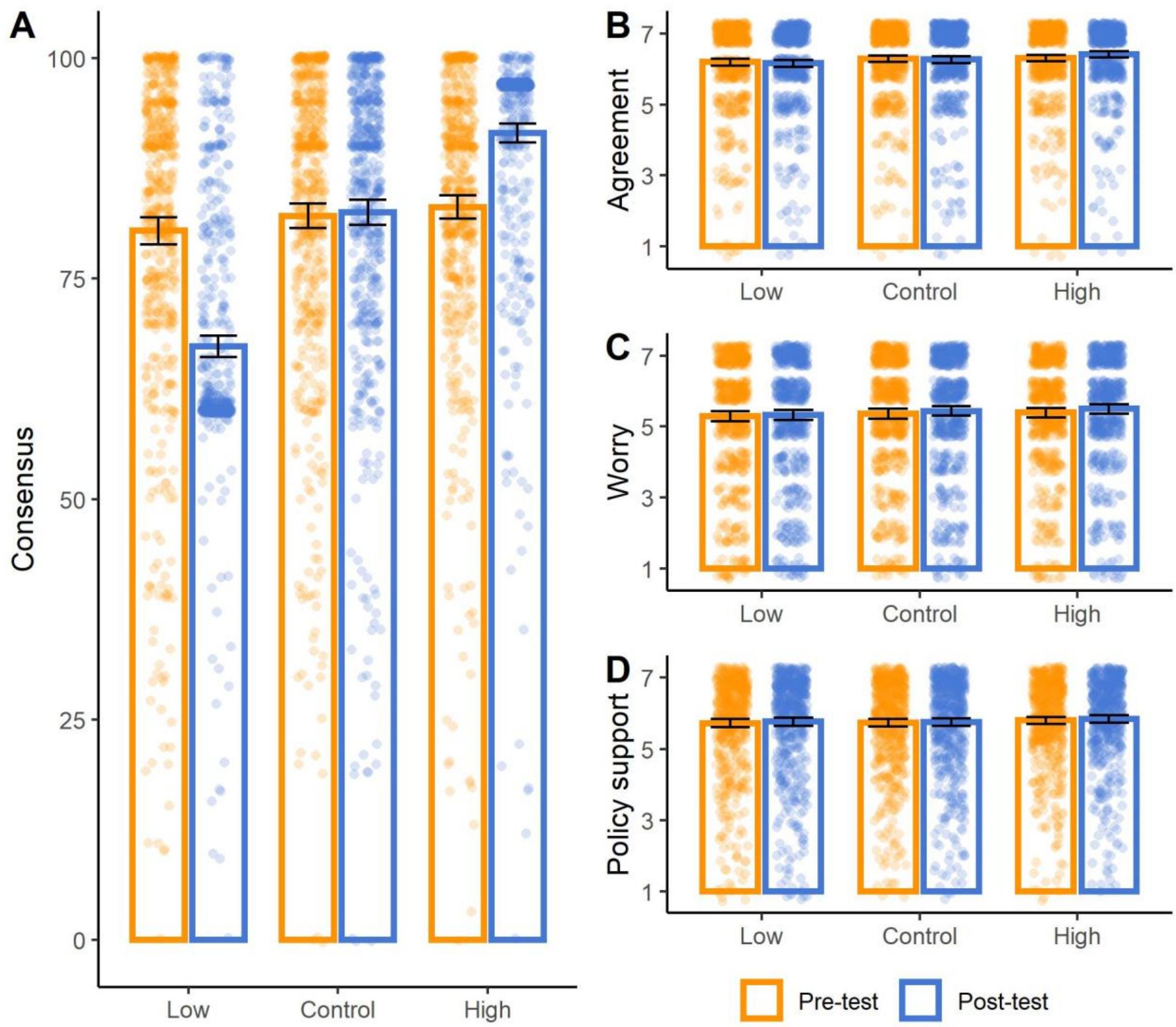

Figure 2. Pre- and post-test means across experimental conditions for: perceived scientific consensus on COVID-19 representing a PHEIC (A), personal agreement that COVID-19 is a PHEIC (B), worry over COVID-19 (C) and support for policies to limit the spread of COVID-19 (D). *Note*: Jittered points represent the underlying data distribution.

Following from van der Linden et al. (2019; 2015), our test of the Gateway Belief Model focuses on individual-level *change* in key variables[2] (see also, van der Linden, Leiserowitz, & Maibach, 2017). That is, each variable in the model represents the difference between pre- and post-treatment scores (see Table 4). Before reporting the results of path models, we first report the main effects of the experimental manipulation on such change (post-pre) in perceived consensus, agreement, worry, and policy support responses (Table 5)[3].

Briefly, all conditions differed significantly in terms of mean change in perceived consensus, and the mean change in reported personal agreement was significantly larger in the high consensus message condition compared to the low and control conditions.

These results show that reading a high (*d* = 0.80) or low consensus message (*d* = 1.04), relative to a control message, significantly and substantially increases or decreases perceptions of scientific consensus regarding COVID-19 representing a PHEIC. Reading a high consensus message also increases reported personal agreement that COVID-19 is a PHEIC (*d* = 0.20), compared to a low or control message.

While there were no main effects of experimental condition on worry or policy support, we note that tests of mediation have more power than the test of the total effect (O'Rourke & MacKinnon, 2015; van der Linden, Leiserowitz, & Maibach, 2017). On that basis we proceeded to examine the mediated effects of the experimental condition and changes in perceived consensus on policy support, via agreement and worry, using a structural equation modelling (SEM) approach. We reiterate that this was our pre-registered analysis.

Table 5. Main effects of condition on post-pre difference scores and pairwise differences

Variable	ANOVA			Post hoc			
	df	F	η^2	Group 1	Group 2	M_{diff}	Cohen's *d*
Consensus	(2,1795)	436.31***	.327	low	control	13.55***	1.04
				low	high	21.50***	1.42
				control	high	7.95***	.80
Agreement	(2,1797)	7.03***	.008	low	control	.01	.02
				low	high	.14**	.20
				control	high	.13**	.19
Worry	(2,1797)	1.42	.002	low	control	.04	.05
				low	high	.06	.09
				control	high	.02	.04
Policy support	(2,1796)	0.28	.000	low	control	-.01	-.04
				low	high	.00	.01
				control	high	.02	.05

** $p < .01$, *** $p < .001$. Tukey's post hoc test.

The impact of a high consensus message

We constructed a structural equation model reflecting the relationships outlined by van der Linden et al. (2019): the reading of a high consensus (vs control) message predicts pre-post changes in perceived scientific consensus, which in turn predicts changes in policy support, with this effect mediated via shifts in personal agreement and worry (see Figure 3). This model fitted the pooled data well by conventional standards, $X^2(4) = 3.29$, $p = .510$; CFI = 1.00; RMSEA = .000 [.000, .041]; SRMR = .014.

Direct and indirect (i.e. mediated) effects are reported in Table 6. In line with prior research, we find that reading a message outlining a high level of scientific consensus leads to significant increases in perceptions of consensus, β = 0.374, 95%CI [0.330, 0.413]. These changes are associated with an increase in personal agreement, β = 0.139, [0.056, 0.236], which in turn predicts increases in support for related policies, β = 0.131 [0.025, 0.246],, resulting in a significant mediated effect of the consensus message on policy support via personal agreement with the consensus position, $\beta_{indirect} = 0.007$ [0.002, 0.018]. Put another way, *message-induced* increases in perceived consensus were associated with increases in personal agreement, which in turn were associated with increases in policy support. In unstandardized terms, the model indicates that reading a high consensus message (vs control) leads to an eight percentage point increase in perceived scientific consensus ($b = 7.94$ [6.82, 9.09]). Such a shift is associated with a 0.07 increase on the 1-7 personal agreement scale ($b = 0.009$ [0.003, 0.015]). An eight percentage point increase in perceived consensus is also associated with a 0.008 increase in policy support on the 1-7 index, mediated via personal agreement (unstandardized mediated effect of consensus on policy via agreement: $b = 0.001$ [0.000,0.001]). This effect, while statistically significant, can be considered small in practical terms, a point we will return to in the discussion. In contrast to results from the climate change domain (van der Linden et al., 2019), we find that experimentally-induced changes in perceived consensus do not significantly predict change in worry over COVID-19, and nor does worry predict policy support.

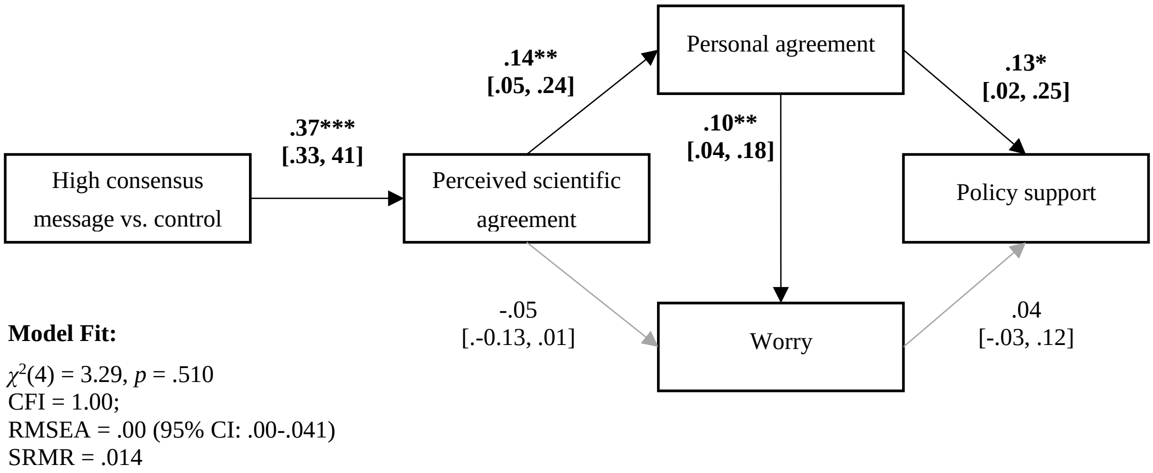

Figure 3. Gateway Belief Model applied to COVID-19 attitudes. Other than the experimental manipulation, variables in the model represent pre-post change scores. *Note*. Standardized coefficients [95% confidence interval] shown; grey arrows indicate non-significant effects; $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 6. Direct and indirect effects of a high (vs control) message and change in perceived consensus in the GBM.

Effects	Path	β	95CI
Direct	Exp → Con	**.374**	**[.330, .413]**
	Con → Agree	**.139**	**[.056, .236]**
	Agree → Worry	**.104**	**[.036, .179]**
	Con → Worry	-.048	[-.130, .011]
	Agree → Policy	**.131**	**[.025, .246]**
	Worry → Policy	.039	[-.033, .118]
Indirect	Con → Agree → Policy	**.018**	**[.006, .046]**
	Con → Worry → Policy	-.002	[-.011, .001]
	Con → Agree → Worry → Policy	.001	[.000, .003]
	Con total indirect	**.017**	**[.003, .045]**
	Exp → Con → Agree → Policy	**.007**	**[.002, .018]**
	Exp → Con → Worry → Policy	-.001	[-.004, .000]
	Exp → Con → Agree → Worry → Policy	.000	[.000, .001]
	Exp total indirect	**.006**	**[.001, .017]**

Note: Exp = Experimental manipulation, Con = Perceived scientific consensus. Bold values indicate bootstrapped 95% confidence intervals (BCa, 5000 samples) does not include zero.

As per our pre-registration, we also fitted a saturated model in which additional paths were specified: direct effects of the experimental manipulation on all other variables in the model and a direct effect of perceived consensus on policy support. None of these additional paths were significant and all other effects were comparable to the results reported here (see Supplementary Information, Appendix 5).

The impact of a low consensus message

When examining the impact of a low (vs control) consensus message, we find that our data again fits the mediation model outlined in Figure 3 well, $X^2(4) = 3.27$, $p = .513$; CFI = 1.00; RMSEA = .000 [.000, .041]; SRMR = .01. Estimation of direct effects in the model revealed that exposure to a low consensus message significantly predicted decreases in perceived consensus (β = -.46, $p < .001$, 95% CI [-.51, -.41]), however changes in perceived consensus were not a significant predictor of change in personal agreement (β = .05, $p = .10$, 95% CI [-.01, 11]) or worry (β = .02, $p = .52$, 95% CI [-.04, -.08]), and had no significant indirect effects on policy support (full results are reported in Supplementary Information, Table S7).

Exploratory moderation by political ideology

As previous studies in the climate domain have indicated that some effects in the GBM vary by political ideology (van der Linden et al., 2019), we examined political ideology as a moderator of the main effects of experimental condition on difference scores and path coefficients in the GBM path model. We found no evidence that political ideology moderates any reported effects (full results in Supplementary information, Appendix 6).

Discussion

Across two studies we report correlational and experimental support for the GBM in the context of COVID-19: Perceptions of scientific consensus on the COVID-19 threat are linked to personal agreement and worry about the issue (Study 1 only) which, in turn, are linked to support for specific policies aiming to control the spread of the virus.

Our Study 1 hypothesis was supported in all individual samples. Our experimental test of the model in Study 2 provided overall support for the model. In a large UK sample, experimentally induced increases in perceived scientific consensus regarding the threat posed by COVID-19 predicted increases in personal agreement with the same claim, and this in turn predicted increases in support for policies that aim to restrict the spread of the virus. This result aligns with findings from the climate change domain (van der Linden et al., 2019; van der Linden, Leiserowitz, et al., 2015) and suggests that communication of the scientific consensus has a role to play in garnering public support for policies to mitigate the spread of COVID-19. The finding that people update their perceptions of the scientific consensus that COVID-19 is a public health emergency—regardless of politics—is not trivial because it adds to a growing evidence base that belief polarization is less likely to occur than initially thought (e.g., Guess & Coppock, 2020; Kuhn & Lao, 1996; Wood & Porter, 2019).

However, we did not find that changes in perceived consensus directly predict changes in worry over COVID-19. We do find that worry is predicted by personal agreement, suggesting that the effect of consensus perceptions on worry is largely mediated via personal agreement. It is possible that this is due to the aligned wording of our consensus and agreement items which both specifically reference COVID-19 representing a PHEIC, while the worry item captured overall worry over the virus.

The weaker effect (Study 1) or lack of an effect (Study 2) of worry on policy support also contrasts with results in the climate domain, where concern and worry over climate change are well-established predictors of support for climate policies (Bouman et al., 2020; Smith & Leiserowitz, 2014; van der Linden et al., 2019). However, in other policy domains the role of affective risk perceptions is less clear. For example, in the US following 9/11, worry and anxiety over terrorism was negatively associated with support for military initiatives and overseas engagement and did not significantly predict support for immigration controls (while perceived threat of terrorism was a positive predictor; Huddy et al., 2005). More research is needed to understand the role of affective risk perceptions, such as worry, and their relation to specific policies about COVID-19. For example, research has shown that risk perceptions in general do correlate with people's self-reported compliance with public health guidelines (Dryhurst et al., 2020; Schneider et al., 2021).

We also find that experimentally induced *decreases* in perceived consensus do not have a subsequent impact on personal agreement or worry, and hence no indirect effect on policy support. While this is a positive finding for those concerned about actors undermining the scientific consensus, it does raise the question of how decreases in perceived consensus fit into the GBM. Our results in this regard align with the findings of Kerr and Wilson (2018) who reported that messages relating a high (97%) and low (63%) level of consensus among climate scientists had essentially equal but opposing effects on perceived consensus (compared to a control group), however only the high consensus message had a significant indirect effect on personal belief in human-caused climate change mediated via shifts in perceived consensus. Taken together these results raise the possibility that there is a non-linear relationship between numerical estimates of the existing level of scientific consensus and the subjective sense of agreement (see also Aklin & Urpelainen, 2014; Johnson, 2017).

Our results provide the first empirical evidence that scientific consensus information can shift COVID-19 attitudes and, in turn, policy support. Thus, we find support for Van Bavel et al.'s (2020) suggestion that consensus information could be used to build support for public health policies to minimize the impact of COVID-19. In terms of applying the GBM in COVID-19 communications, our experiment was a very conservative test of the model, examining the impact of a singular sentence on attitudes. This is reflected in the relatively small effect sizes reported for the main and indirect effects of the experimental intervention. The current results are comparable to findings from consensus messaging studies in the climate domain. For example, van der Linden et al (2019) report a $d = .09$ main effect of the consensus message on policy support. More broadly, a meta-analysis of climate messaging effects conducted by Rode et al., (2021) reports that policy attitudes are more difficult to experimentally shift than other climate-related attitudes. The pooled effect of expert consensus studies on climate attitudes (g = 0.09) was robust though relatively small, but in line with the meta-analytic effect size for all climate messaging interventions examined in the analysis ($g = 0.08$), from moral frames to psychological distance manipulations. In addition, messaging studies examining COVID-19 policy support have also reported limited effects. For example, Farjam et al. (2021) report that attributing policy interventions and their justification to a scientist has an no significant effect on support. However we would note that the main aim of the current study was not simply to shift policy support but to test the causal role of changes in perceived scientific consensus in policy attitudes, as outlined in the GBM. The very brief and simple nature of the messages used in Study 2 does make them very scalable via social and mainstream media. The effects reported in the current study also result from just a single exposure. Implemented at scale small messaging effects can have a discernible impact on public opinion (see discussion in: Landrum & Slater, 2020; Rode et al., 2021; van der Linden et al., 2019). More engaging and repeated consensus messaging campaigns incorporating visual elements or humor may prove more effective in shifting beliefs for those wanting to do so (Brewer & McKnight, 2017; Clarke et al., 2020; Goldberg, van der Linden, et al., 2020; Harris et al., 2019). Moreover, even when consensus messages do not directly shift policy support, they can still help counter the spread of misinformation (Maertens et al., 2020; van der Linden, Leiserowitz, Rosenthal, et al., 2017).

As mentioned, we did not find evidence of backfire or polarization effects. The "cultural cognition of scientific consensus" hypothesis suggests that exposure to expert consensus cues on contested issues should polarize partisans further (Kahan et al., 2011). Although studies have noted an association between political ideology and COVID risk perceptions or policy support (Calvillo et al., 2020; Kerr et al., 2021; Mellon et al., 2020), we did not find political orientation to be a moderating factor in our experiment. This suggests that individuals across the political spectrum are equally influenced by COVID-19 consensus messages. However, we must acknowledge that we cannot generalize this finding beyond the UK; it is possible that in countries with greater political polarization over COVID-19 mitigation policies, such as the US, political orientation might have a moderating influence. Further international research is required to confirm consensus messaging as a 'politically neutral' approach to COVID-19 communications.

Our finding that decreases in perceived consensus did not predict a lack of policy support should not invite complacency regarding the publics' perception of scientific opinion on COVID-19. More direct efforts to attack perceptions of scientific consensus on specific issues (e.g., COVID-19 vaccine safety) could undermine support for COVID-19 policies. Groups opposed to certain policies for ideological or financial reasons may well seek to cast doubt on scientific consensus to weaken public support for those policies, as has been documented in relation to issues such as climate change and the carcinogenicity of tobacco (Diethelm & McKee, 2009; Oreskes & Conway, 2010).

Indeed in the US and UK, interest groups have cast aspersions on the science behind COVID-19 claims (Ball, 2020). Russian Twitter bots have already spread information undermining the scientific consensus on vaccine efficacy (Broniatowski et al., 2018), and there is evidence that similar tactics are being used to undermine scientific consensus regarding COVID-19 (Marineau, 2020; Memon & Carley, 2020). Recent work on inoculation—warning individuals of disinformation strategies *before* exposure to misleading information—offers some hope for effective pre-bunking of efforts to undermine the scientific consensus (Cook et al., 2017; Lewandowsky & van der Linden, 2021). We also recognize that unlike other publicly debated scientific issues, such as vaccination and climate change, COVID-19 is a new and emerging issue. Thus, even where there is apparent scientific consensus, the body of research upon which this is based may be limited and there is certainly capacity for the consensus position to change (see Martin et al., 2020).

Strengths of the current studies include the use of large, broadly representative samples from multiple countries (in Study 1) and a pre-registered experimental approach to test causal paths. However we must acknowledge some limitations. The use of single item measures for some constructs, though consistent with prior research (van der Linden et al., 2019), will have introduced measurement error into our models. Future researchers should consider the use of multi-item scales to better capture the constructs outlined in the GBM. The experiment was also embedded in a larger survey and preceded by question blocks which included other items on COVID-19 risk perceptions and attitudes. Thus it is possible that these items primed responses in our experiment, however any such effects would be consistent across conditions. Lastly, while our cross-sectional study reported consistent results across a number of countries, in two different languages, our experiment was only conducted with a UK sample and therefore we cannot be certain that these results will generalize to other contexts, particularly non-WEIRD (White, Educated, Industrialized, Rich, and Democratic; Henrich et al., 2010) samples.

In conclusion, we offer correlational and experimental support for the GBM in the context of COVID-19 attitudes: perceptions of scientific consensus are tied to individuals' beliefs about the threat posed by the COVID-19 virus and support for policies to limit the spread of the virus. In agreement with previous research, we note an asymmetry in that increasing perceptions of consensus has a greater indirect effect on policy support than decreasing perceptions does in the opposite direction. Policy makers and public health communicators should be aware that the general publics' idea of "whether scientists agree" has a significant impact on personal attitudes about the virus and subsequently their support for related policies to curb its spread and impact.

Endnotes

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[1] We cannot rule out the possibility that some UK participants held both Respondi and Prolific accounts and participated on both platforms. We acknowledge this as limitation, but also note that, given the size of each platforms' UK participant panel, and the fact that only a small random subset of eligible participants are invited, the likelihood of such occurrences is small.

[2] Before examining pre-post differences, we first fitted the cross-sectional model from Study 1 to pre-test responses. The results were consistent with Study 1 (see supplementary information, Table S6).

[3] We conducted one-way ANOVAs to examine the relationship between condition assignment and pre-test scores on all variables. There was a significant effect of condition on pre-test consensus estimates, $F(2, 1724) = 3.45$, $p = .032$, $\eta^2 = 0.004$. Tukey's post hoc tests revealed a significant difference between the mean consensus estimates in the low and high conditions, with participants in the high consensus condition estimating, on average, slightly higher levels of scientific consensus *prior* to the manipulation ($M_{\text{diff}} = 2.45$, $p = .038$, $d = -0.14$). No other significant differences were detected. As there was a significant difference between pre-test mean consensus estimates across experimental conditions, we also conducted a series of ANCOVA models examining the effect of condition on post-test scores for all variables, *controlling for pretest estimates*. The pattern of significant results was identical (see Supplementary Information, Appendix 3).

Data availability

Data and R analysis code are available at:

https://osf.io/gk9uv/?view_only=a508b50750074b1ab178c92984c2ed3e

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Communicating expert consensus increases personal support for COVID-19 mitigation policies: Supplementary material

Appendix 1: Study 1 full results

Table S1. Study 1 Descriptive statistics and intercorrelations, by sample.

Sample	Variable	*M*	*SD*	Correlation matrix			
				Consensus	Agreement	Worry	Policy (WFH)
Pooled sample	Consensus	86.21	16.35				
	Agreement	4.57	0.81	0.5***			
	Worry	5.85	1.38	0.38***	0.48***		
	Policy (WFH)	5.77	1.59	0.37***	0.45***	0.36***	
	Policy (LD)[1]	5.79	1.66	0.37***	0.46***	0.43***	0.70***
Spain	Consensus	87.13	15.68				
	Agreement	4.53	0.85	0.42***			
	Worry	6.11	1.26	0.39***	0.44***		
	Policy (WFH)	4.89	1.87	0.28***	0.24***	0.21***	
Ireland	Consensus	85.52	17.81				
	Agreement	4.59	0.79	0.45***			
	Worry	6.02	1.32	0.37***	0.4***		
	Policy (WFH)	6.08	1.28	0.35***	0.35***	0.29***	
	Policy (LD)	5.62	1.65	0.25***	0.26***	0.3***	0.55***
Mexico	Consensus	84.47	16.80				
	Agreement	4.48	0.83	0.47***			
	Worry	6.06	1.35	0.41***	0.49***		
	Policy (WFH)	5.35	1.85	0.31***	0.34***	0.33***	
UK (Prolific; Apr)	Consensus	90.42	11.37				
	Agreement	4.74	0.63	0.44***			
	Worry	5.99	1.20	0.31***	0.45***		
	Policy (WFH)	6.39	1.09	0.31***	0.43***	0.38***	
	Policy (LD)	6.34	1.19	0.27***	0.43***	0.4***	0.65***
UK (Prolific; May)	Consensus	89.09	13.01				
	Agreement	4.68	0.68	0.48***			
	Worry	5.72	1.40	0.29***	0.45***		
	Policy (WFH)	6.04	1.38	0.31***	0.45***	0.37***	
	Policy (LD)	5.88	1.60	0.28***	0.43***	0.38***	0.67***
UK (Respondi; Apr)	Consensus	85.49	17.08				
	Agreement	4.57	0.84	0.50***			
	Worry	5.91	1.30	0.37***	0.45***		
	Policy (WFH)	5.97	1.43	0.44***	0.5***	0.38***	
	Policy (LD)	5.94	1.56	0.41***	0.46***	0.43***	0.69***
	Consensus	83.22	18.36				
	Agreement	4.48	0.87	0.46***			

UK (Respondi; May)	Worry	5.60	1.51	0.34***	0.5***		
	Policy (WFH)	5.70	1.55	0.40***	0.51***	0.4***	
	Policy (LD)	5.56	1.76	0.35***	0.45***	0.42***	0.70***
US	Consensus	82.58	19.30				
	Agreement	4.39	0.95	0.64***			
	Worry	5.58	1.60	0.57***	0.63***		
	Policy (WFH)	5.22	1.83	0.49***	0.61***	0.58***	
	Policy (LD)	5.11	2.01	0.50***	0.60***	0.57***	0.79***

Notes: [1]Exludes Spain and Mexico. WFH = Work from home; LD = Lockdown. ***p < .001

Table S2. Fit indices for model predicting support for Work from Home policy, fitted to data from individual samples.

Sample	$X^2(1)$	CFI	SRMR	RMSEA [95CI]
Pooled sample	424.06	.967	.039	.168 [.154, .181]
Spain	21.52***	.942	.049	.179 [.119, .249]
Ireland	18.04***	.943	.049	.192 [.121, .274]
Mexico	11.15***	.976	.035	.135 [.072, .211]
UK (Prolific; Apr)	7.48**	.983	.029	.111 [.047, .190]
UK (Prolific; May)	9.06**	.989	.024	.093 [.045, .152]
UK (Respondi; Apr)	36.45***	.951	.049	.215 [.159, .278]
UK (Respondi; May)	32.87***	.958	.046	.197 [.143, .258]
US	3.20	.997	.014	.067 [.000, .155]

**p < .01, ***p < .001

Table S3. Parameter estimates for model predicting support for Work from Home policy, for all samples.

Sample	Path	β	*b*	95CI
Pooled sample	a1	0.50***	0.02	[0.02, 0.03]
	a2	0.19***	0.02	[0.01, 0.02]
	d	0.38***	0.66	[0.62, 0.70]
	b1	0.29***	0.57	[0.53, 0.61]
	b2	0.15***	0.18	[0.16, 0.19]
	c	0.17***	0.02	[0.02, 0.02]
	Indirect	0.20***	0.02	[0.02, 0.02]
	Total	0.37***	0.04	[0.03, 0.04]
Spain	a1	0.42***	0.02	[0.02, 0.03]
	a2	0.25***	0.02	[0.01, 0.03]
	d	0.33***	0.48	[0.33, 0.66]
	b1	0.12**	0.27	[0.10, 0.45]
	b2	0.08	0.12	[0.00, 0.23]
	c	0.20***	0.02	[0.01, 0.03]
	Indirect	0.08***	0.01	[0.00, 0.02]
	Total	0.28***	0.03	[0.03, 0.04]
Ireland	a1	0.45***	0.02	[0.02, 0.03]
	a2	0.24***	0.02	[0.01, 0.03]
	d	0.29***	0.48	[0.32, 0.67]
	b1	0.21***	0.33	[0.17, 0.52]
	b2	0.13**	0.13	[0.04, 0.23]
	c	0.21***	0.01	[0.01, 0.02]
	Indirect	0.14***	0.01	[0.01, 0.01]
	Total	0.35***	0.03	[0.02, 0.03]
Mexico	a1	0.46***	0.02	[0.02, 0.03]
	a2	0.24***	0.02	[0.01, 0.03]
	d	0.38***	0.61	[0.43, 0.80]
	b1	0.18***	0.41	[0.21, 0.61]
	b2	0.19***	0.26	[0.14, 0.39]
	c	0.15**	0.02	[0.01, 0.03]
	Indirect	0.16***	0.02	[0.01, 0.02]
	Total	0.31***	0.03	[0.03, 0.04]
UK (Prolific; Apr)	a1	0.44***	0.02	[0.02, 0.03]
	a2	0.14**	0.02	[0.01, 0.02]
	d	0.38***	0.73	[0.53, 0.96]
	b1	0.28***	0.49	[0.29, 0.70]
	b2	0.22***	0.20	[0.12, 0.28]
	c	0.12**	0.01	[0.00, 0.02]
	Indirect	0.19***	0.02	[0.01, 0.02]
	Total	0.31***	0.03	[0.02, 0.04]
UK (Prolific; May)	a1	0.48***	0.03	[0.02, 0.03]
	a2	0.10**	0.01	[0.00, 0.02]

	d	0.40***	0.81	[0.63, 0.99]
	b1	0.32***	0.65	[0.46, 0.84]
	b2	0.20***	0.20	[0.13, 0.27]
	c	0.10**	0.01	[0.00, 0.02]
	Indirect	0.21***	0.02	[0.02, 0.03]
	Total	0.31***	0.03	[0.03, 0.04]
UK (Respondi; Apr)	a1	0.52***	0.02	[0.02, 0.03]
	a2	0.18***	0.01	[0.01, 0.02]
	d	0.37***	0.58	[0.44, 0.73]
	b1	0.32***	0.55	[0.39, 0.71]
	b2	0.15***	0.17	[0.09, 0.25]
	c	0.22***	0.02	[0.01, 0.02]
	Indirect	0.22***	0.02	[0.01, 0.02]
	Total	0.44***	0.04	[0.03, 0.04]
UK (Respondi; May)	a1	0.46***	0.02	[0.02, 0.03]
	a2	0.14***	0.01	[0.01, 0.02]
	d	0.44***	0.76	[0.62, 0.93]
	b1	0.33***	0.60	[0.46, 0.74]
	b2	0.17***	0.18	[0.11, 0.25]
	c	0.19***	0.02	[0.01, 0.02]
	Indirect	0.21***	0.02	[0.01, 0.02]
	Total	0.40***	0.03	[0.03, 0.04]
US	a1	0.64***	0.03	[0.03, 0.04]
	a2	0.28***	0.02	[0.02, 0.03]
	d	0.45***	0.76	[0.59, 0.92]
	b1	0.37***	0.7	[0.52, 0.89]
	b2	0.30***	0.35	[0.24, 0.45]
	c	0.08	0.01	[0.00, 0.02]
	Indirect	0.41***	0.04	[0.03, 0.05]
	Total	0.49***	0.05	[0.04, 0.05]

**$p < .01$, ***$p < .001$

Appendix 2

Study 1: Predicting support for a policy of continued lockdown

In addition to the key dependent variable examined in the main text—support for a work from home policy—we also asked participants in the UK, US, and Ireland samples to indicate their level of support for a related policy: *I believe the current lockdown should continue for at least another 3 weeks* (range: *Not at all* (1) to *Very much* (7); descriptive statistics reported in Table S1).

We report here the results of models testing the fit of the GBM in predicting continued lockdown report using the same specifications outlined in the main text.

Table S4. Fit indices for model predicting support for continued lockdown, fitted to data from pooled and individual samples.

Sample	$X^2(1)$	CFI	SRMR	RMSEA [95CI]
Pooled sample	249.94***	.978	.033	.142 [.128, .157]
Ireland	6.79**	.981	.029	.104 [.042, .184]
UK (Prolific; Apr)	2.36	.997	.016	.050 [0.00, .136]
UK (Prolific; May)	5.09*	.994	.018	.065 [.019, .126]
UK (Respondi; Apr)	29.47***	.959	.044	.192 [.136, .254]
UK (Respondi; May)	18.25***	.976	.035	.143 [.090, .204]
US	6.93**	.994	.019	.100 [.041, .176]

**$p < .01$, ***$p < .001$

As with support for Work from Home policy, we also report path coefficients estimated from a saturated model in Table S5.

Table S5. Parameter estimates for model predicting support for continued lockdown, for all samples.

Sample	Path	beta	b	95CI
Pooled sample	a1	0.51***	0.02	[0.02, 0.03]
	a2	0.17***	0.01	[0.01, 0.02]
	d	0.40***	0.70	[0.66, 0.74]
	b1	0.27***	0.56	[0.52, 0.61]
	b2	0.24***	0.29	[0.27, 0.31]
	c	0.14***	0.01	[0.01, 0.02]

	Indirect	0.23***	0.02	[0.02, 0.02]
	Total	0.37***	0.04	[0.04, 0.04]
Ireland	a1	0.45***	0.02	[0.02, 0.02]
	a2	0.24***	0.02	[0.01, 0.03]
	d	0.29***	0.49	[0.31, 0.67]
	b1	0.12*	0.25	[0.07, 0.45]
	b2	0.21***	0.26	[0.15, 0.38]
	c	0.12*	0.01	[0.00, 0.02]
	Indirect	0.13***	0.01	[0.01, 0.02]
	Total	0.25***	0.02	[0.02, 0.03]
UK (Prolific; Apr)	a1	0.44***	0.02	[0.02, 0.03]
	a2	0.14***	0.02	[0.01, 0.02]
	d	0.38***	0.73	[0.53, 0.96]
	b1	0.28***	0.53	[0.34, 0.76]
	b2	0.26***	0.25	[0.17, 0.34]
	c	0.06	0.01	[0.00, 0.02]
	Indirect	0.20***	0.02	[0.02, 0.03]
	Total	0.27***	0.03	[0.02, 0.04]
UK (Prolific; May)	a1	0.48***	0.03	[0.02, 0.03]
	a2	0.10**	0.01	[0.00, 0.02]
	d	0.40***	0.81	[0.62, 1.00]
	b1	0.29***	0.69	[0.49, 0.90]
	b2	0.23***	0.27	[0.19, 0.35]
	c	0.07*	0.01	[0.00, 0.02]
	Indirect	0.21***	0.03	[0.02, 0.03]
	Total	0.28***	0.03	[0.03, 0.04]
UK (Respondi; Apr)	a1	0.50***	0.02	[0.02, 0.03]
	a2	0.18***	0.01	[0.01, 0.02]
	d	0.36***	0.56	[0.42, 0.71]
	b1	0.24***	0.45	[0.30, 0.63]
	b2	0.25***	0.3	[0.21, 0.40]
	c	0.19***	0.02	[0.01, 0.02]
	Indirect	0.21***	0.02	[0.01, 0.03]
	Total	0.41***	0.04	[0.03, 0.04]
UK (Respondi; May)	a1	0.46***	0.02	[0.02, 0.03]
	a2	0.14***	0.01	[0.00, 0.02]
	d	0.44***	0.76	[0.61, 0.92]
	b1	0.27***	0.55	[0.39, 0.72]
	b2	0.23***	0.27	[0.18, 0.35]
	c	0.14***	0.01	[0.01, 0.02]
	Indirect	0.20***	0.02	[0.02, 0.02]
	Total	0.35***	0.03	[0.03, 0.04]
US	a1	0.64***	0.03	[0.03, 0.04]
	a2	0.28***	0.02	[0.02, 0.03]
	d	0.45***	0.76	[0.59, 0.93]
	b1	0.35***	0.74	[0.56, 0.94]

	b2	0.29***	0.37	[0.25, 0.48]
	c	0.11**	0.01	[0.00, 0.02]
	Indirect	0.39***	0.04	[0.03, 0.05]
	Total	0.50***	0.05	[0.04, 0.06]

Note: Bootstrapped 95% Confidence intervals based on 5000 samples (Bias corrected accelerated).

*p < .05, **p < .01, ***p < .001.

Appendix 3

Study 2: ANCOVA model results

As there was difference between the high and low condition pre-test consensus estimates, we examined post-test score differences between conditions with ANCOVA models controlling for pre-test scores. Results indicated message condition had a significant effect on post-test consensus estimates ($F(2, 1723) = 622.77$, $p < .001$, $\eta^2_G = 0.42$) and post-test reported agreement that COVID-19 is a PHEIC ($F(2, 1724) = 9.38$, $p < .001$, $\eta^2_G = 0.01$), but not worry or policy support.

Pairwise comparisons of estimated marginal means (with Holm correction for multiple testing) revealed that post-test consensus estimates differed significantly between all groups; estimates in the control condition were higher than those in low condition and estimates in the high condition higher than both the low and control conditions ($M_{diff:low-control} = 14.21$, $p < .001$, $d = -.1.30$; $M_{diff:low-high} = -22.54$, $p < .001$, $d = -2.07$; $M_{diff:control-high} = 8.34$, $p < .001$, $d = -0.76$). Considering differences in mean post-test personal agreement we report that the mean response in the high condition was larger than the mean response in the low ($M_{diff:low-high} = -0.16$, $p < .001$, $d = -0.24$) and control conditions ($M_{diff:control-high} = -0.13$, $p < .01$, $d = -0.19$). No other significant main effects of message condition were detected.

Appendix 4

Study 2: Cross-sectional test of the GBM

Table S6. Parameter estimates for cross-sectional test of the GBM using Study 2 pre-test responses.

Path	β	*b*	95% CI
Con → Agree	.609	.040	[.036, .044]
Con → Worry	.151	.014	[.008, .020]
Agree → Worry	.403	.585	[.488, .679]
Agree → Policy	.322	.369	[.296, .438]
Worry → Policy	.346	.273	[.231, .315]
Con → Policy	.166	.012	[.008, .017]
Con → Agree → Policy	.196	.015	[.012, .018]
Con → Worry → Policy	.052	.004	[.002, .006]
Con → Agree → Worry → Policy	.085	.006	[.005, .008]
Total indirect	.333	.025	[.022, .029]
Total	.499	.037	[.033, .042]

Appendix 5

Study 2: Full results of experimental test of the GBM

The figures below outline the path model specification for the GBM model reported in the main text (Figure S1) and an additional model incorporating direct effects of experimental manipulation and perceived consensus on all downstream variables (Figure S2). Standardized coefficients for both models, examining the high vs control and low vs control contrasts, are shown in Table S7.

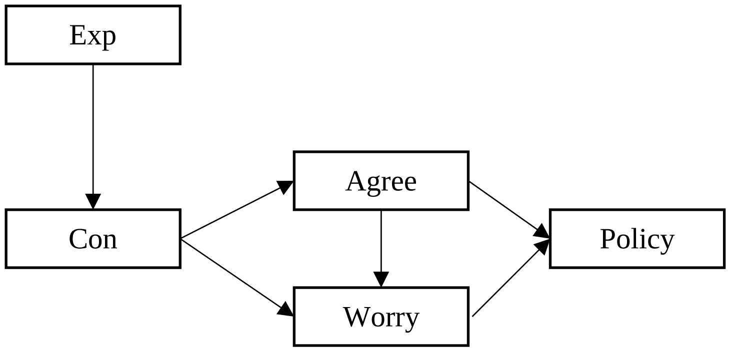

Figure S1. Specification for unsaturated model.

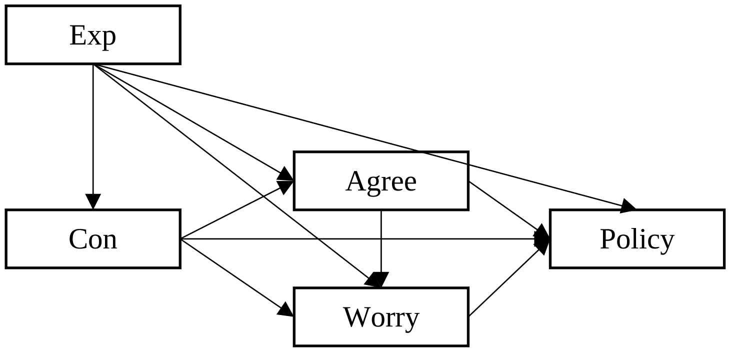

Figure S2. Model specification for saturated model.

Table S7.

Standardized direct, indirect and total effects for high vs control and low vs control contrasts in saturated and unsaturated models.

Path	High vs control				Low vs control			
	Unsaturated		Saturated		Unsaturated		Saturated	
	β	95CI	β	95CI	β	95CI	β	95CI
Exp → Con	**.374**	**[.330, .413]**	**.374**	**[.329, .412]**	**-.462**	**[-.509, -.410]**	**-.462**	**[-.510, -.411]**
Con → Agree	**.139**	**[.056, .236]**	**.123**	**[.038, .229]**	.053	[-.013, .111]	.059	[-.029, .131]
Exp → Agree			.043	[-.017, .102]			.013	[-.062, .085]
Agree → Worry	**.104**	**[.036, .179]**	**.103**	**[.037, .177]**	**.090**	**[.029, .159]**	**.090**	**[.029, .161]**
Con → Worry	-.048	[-.130, .011]	-.06	[-.146, .005]	.020	[-.035, .079]	.011	[-.060, .084]
Exp → Worry			.034	[-.029, .094]			-.018	[-.089, .048]
Agree → Policy	**.131**	**[.025, .246]**	**.131**	**[.026, .245]**	**.089**	**[.009, .183]**	**.087**	**[.006, .183]**
Worry → Policy	.039	[-.033, .118]	.038	[-.034, .115]	.067	[-.009, .143]	.067	[-.016, .143]
Con → Policy			-.007	[-.098, .068]			.048	[-.035, .119]
Exp → Policy			.016	[-.050, .080]			.047	[-.028, .120]
Con → Agree → Policy	**.018**	**[.006, .046]**	**.016**	**[.005, .046]**	.005	[.000, .014]	.005	[-.001, .017]
Con → Worry → Policy	-.002	[-.011, .001]	-.002	[-.012, .001]	.001	[-.002, .009]	.001	[-.004, .009]
Con → Agree → Worry → Policy	.001	[.000, .003]	.000	[.000, .003]	.000	[.000, .002]	.000	[.000, .002]
Con total indirect	**.017**	**[.003, .045]**	**.014**	**[.002, .043]**	.006	[-.001, .017]	.006	[-.002, .019]
Con Total			.007	[-.084, .089]			.054	[-.026, .125]
Exp → Con → Agree → Policy	**.007**	**[.002, .018]**	**.006**	**[.002, .017]**	-.002	[-.006, .000]	-.002	[-.008, .000]
Exp → Con → Worry → Policy	-.001	[-.004, .000]	-.001	[-.004, .000]	-.001	[-.004, .001]	.000	[-.004, .002]
Exp → Con → Agree → Worry → Policy	.000	[.000, .001]	.000	[.000, .001]	.000	[-.001, .000]	.000	[-.001, .000]
Exp total indirect	**.006**	**[.001, .017]**	**.005**	**[.001, .016]**	-.003	[-.008, .000]	-.003	[-.009, .001]
Exp total			.026	[-.035, .081]			.022	[-.036, .079]

Note: Exp = Experimental manipulation, Con = Perceived scientific consensus. Bold values indicate bootstrapped 95% confidence interval (BCa, 5000 samples) does not include zero.

Appendix 6

Study 2: Moderating effects of political ideology

As political orientation has been noted as a moderating factor in tests of the GBM in relation to climate change (van der Linden et al., 2019), we conducted exploratory analyses investigating the role of political ideology in the GBM applied to COVID-19 attitudes. For each of the variables in the model, mean post-pre scores were compared between the three experimental and three political groups (left-wing, moderate, and right-wing; see Study 2 methods) in a 3x3 ANOVA. There were no significant interactions between experimental condition and political group (Fs(4, 1714-1715) = .54-2.34, ps > .05, η^2_Gs = .001-.005). In line with results reported in the main text (Table 5), we report a significant main effect of experimental condition on change in perceived consensus ($F(2, 1714) = 376.83$, $p < .001$, $\eta^2_G = .305$) and personal agreement ($F(2,1715) = 7.29$, $p < .001$, $\eta^2_G = .008$). We also identified main effects of political ideology (i.e. independent of experimental condition assignment) when comparing change in perceived consensus ($F(2, 1714) = 6.60$, $p < .01$, $\eta^2_G = .008$), personal agreement ($F(2, 1715) = 3.71$, $p < .01$, $\eta^2_G = .004$), and worry ($F(2, 1715) = 3.12$, $p < .05$, $\eta^2_G = .04$). Pairwise comparisons between groups (Tukey's HSD) revealed that moderates, compared to left-leaning participants, tended overall to exhibit more positive change in perceived consensus ($M_{diff} = -3.04$, $p < .01$, $d = .19$) and personal agreement ($M_{diff} = -.11$, $p < .05$, $d = .14$). Left-wing participants, compared to right-wing participants, tended overall to exhibit greater increases in worry $M_{diff} = -.10$, $p < .01$, $d = .15$). We detected no other significant pairwise differences.

Overall, these exploratory results indicate that while there are some differences in how political groups respond to a consensus message, these effects are consistent across the three conditions in the experiment.

We also examined the role of political ideology in the GBM model by constructing two nested models (specified as in Figure S1): one in which path coefficients were allowed to vary freely between each political group and one in which paths were constrained to be equal between all groups. Likelihood ratio tests indicated that constraining paths to be equal between groups did not significantly reduce fit relative to the unconstrained model in either the high vs control contrast ($\Delta X^2(12) = 2.24$, $p = .06$), or the low vs control contrast ($\Delta X^2(12) = 19.18$, $p = .08$). This indicates that the path coefficients in the model (and by extension, indirect effects) do not significantly differ across political groups.