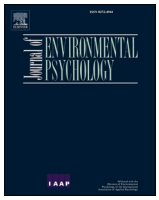
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The Gateway Belief Model: A pre-registered large-scale replication in China

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ABSTRACT

Climate change is a global problem that needs to be addressed, but public support for action remains a challenge. According to the Gateway Belief Model (GBM), emphasizing the scientific consensus on the issue predicts changes in cognitive and emotional responses related to climate change, which in turn predict increased support for public action. However, evidence from non-WEIRD populations is lacking for this model. The current study conducted a confirmatory replication of the GBM for the first time in China using a national quota sample (N = 1506). The results suggest that consensus messaging increased participants' perceived scientific consensus, their beliefs that global warming is happening and human caused, as well as support for public action on global warming. Furthermore, the results partially support the mediation hypothesis of the GBM. Experimentally induced changes in perceived scientific consensus directly predicted subsequent changes in general attitudes toward public actions, support for specific government policies, and behavioral intentions. We further found an interaction between participants' self-reported impact of global warming and the consensus manipulation. Participants less impacted by global warming were more likely to change their perceptions to align with the consensus after being exposed to the consensus message. These findings emphasize the critical role of consensus messaging in enhancing public support for global warming actions in China, especially among those less impacted by global warming.

1. Introduction

With years of record high temperatures and extreme weather (Robinson, Lehmann, Barriopedro, Rahmstorf, & Coumou, 2021; Witze, 2022; Wong, 2023), climate change is an urgent global problem (Roy et al., 2022; Steg, 2018). Its negative impacts on health (Bell, Gasparrini, & Benjamin, 2024; Ebi, Capon, et al., 2021; Ebi, Vanos, et al., 2021; Lüthi et al., 2023) and economic development (Ciscar et al., 2011; Hsiang et al., 2017; Newman & Noy, 2023) further underscore the severity of the crisis. Despite this urgency, research suggests that a strong public consensus on climate change is lacking (Benegal & Scruggs, 2018; Cook, van der Linden, Maibach, & Lewandowsky, 2018; Rainie & Funk, 2015). For example, fewer than half of Americans believe that climate change is caused by humans (Pew, 2023), and only 21% (1 in 5) understand that more than 90% of climate scientists have concluded that humans are causing global warming (Leiserowitz et al., 2024). More generally, public opinion on climate change varies widely around the world (Carman et al., 2024). Research on the impact of communicating scientific consensus information about anthropogenic climate change has been growing in recent years (e.g., see Harris, Sildmäe, Speekenbrink, & Hahn, 2019; Goldberg, Gustafson, van der Linden, Rosenthal, & Leiserowitz, 2022; Kerr & Wilson, 2018; Tschötschel, Schuck, Schwinges, & Wonneberger, 2021; van der Linden, Leiserowitz, & Maibach, 2018; Said, Frauhammer, & Huff, 2022; Orchinik, Dubey, Gershman, Powell, & Bhui, 2023; Većkalov et al., 2024; Vlasceanu et al., 2024). In fact, two recent meta-analyses demonstrated the robust impact of communicating the fact that over 97% of scientists agree that global warming is happening on both perceived scientific consensus and subsequent belief in global warming (Rode et al., 2021; van Stekelenburg, Schaap, Veling, van 't Riet, & Buijzen, 2022).

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1.1. The Gateway Belief Model (GBM)

Importantly, previous studies have shown that communicating scientific consensus information can change people's beliefs related to climate change and their support for taking action on the issue (Bolsen & Druckman, 2018; Ding, Maibach, Zhao, Roser-Renouf, & Leiserowitz, 2011; Goldberg, van der Linden, Ballew, Rosenthal, & Leiserowitz, 2019; Kobayashi, 2018; Lewandowsky, Gignac, & Vaughan, 2013; McCright, Dunlap, & Xiao, 2013; van der Linden, 2021; van der Linden, Leiserowitz, Feinberg, & Maibach, 2015). Yet, insufficient attention has been paid to the psychological processes underlying how consensus interventions work. Accordingly, van der Linden et al. (2015) proposed an integrative model, known as the Gateway Belief Model (GBM), to address this issue. The GBM is a dual-process theory of attitude change, which posits that descriptive norms, such as perceived scientific consensus acts as a "gateway belief" that influences other second-order key cognitions and emotions related to climate change, thereby enhancing support for climate mitigation actions (van der Linden, 2021). Specifically, the GBM (Fig. 1) is a two-stage mediation model where communicating consensus information is hypothesized to boost perceived scientific consensus on human-caused climate change (Stage 1). These changes in perceived consensus information are subsequently hypothesized to change people's beliefs that global warming is happening, human-caused, as well as increase their worry about global warming, which in turn (Stage 2) increase support for public actions indirectly (van der Linden et al., 2015, 2019). In other words, the consensus treatment should have a substantial (corrective) impact on people's (mis)perceptions of the scientific consensus, with increasingly smaller subsequent changes in related beliefs and attitudes (van der Linden, 2021). The GBM has been applied in a wide variety of domains, from COVID-19 (Bialek et al., 2023; Kerr & van der Linden, 2022), and vaccines (Bartoš, Bauer, Cahlíková, & Chytilová, 2022; van der Linden et al., 2015) to GMOs (Bode, Vraga, & Tully, 2021; Dixon, 2016). The literature on the GBM in the context of climate change has especially grown rapidly over the past several years (Bayes, Bolsen, & Druckman, 2023; Bertoldo et al., 2019; Kerr & Wilson, 2018; Said et al., 2022; van der Linden, 2021).

Despite this emerging literature, a variety of open questions and critiques remain, for example, whether the impact of scientific consensus messaging on support for public action is primarily an indirect path or not (van der Linden, 2021). In addition, research frequently examines the "gateway" hypothesis in a piecemeal fashion, conducting separate mediation analyses for only parts of the model (e.g., Bolsen & Druckman, 2018; Goldberg et al., 2019; Kerr & Wilson, 2018; Sloane & Wiles, 2020; Većkalov et al., 2024), which precludes a full and comprehensive test of all mediational stages of the GBM as well as a test of how the proposed variables conceptually relate to one another. Other limitations include potential reliability issues concerning the use of single-items (which can be noisy) and not properly relating pre-post *changes* in scientific consensus to pre-post *changes* in the downstream variables since the GBM is based on a model of *changes* in attitudes (van der Linden, 2021). Finally, most studies are conducted in the US, and although there has been some cross-cultural work (e.g., less consistent findings in Germany where people's understanding of the scientific consensus on climate change is already high; Said et al., 2022), replications in non-WEIRD samples (Western, Educated, Industrialized, Rich, and Democratic; Henrich et al., 2010) are lacking.

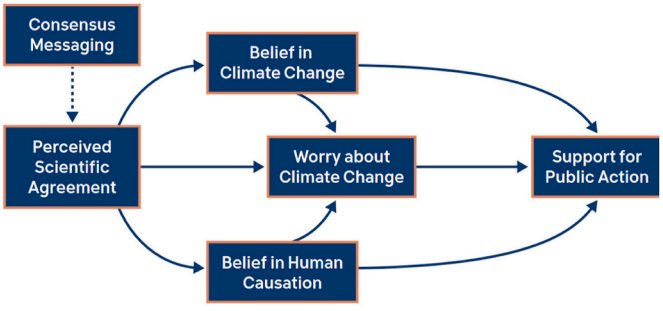


Fig. 1. Gateway Belied Model (GBM) of attitude change adopted from van der Linden (2021) with permission. *Note*: Communicating the scientific consensus changes people's perception of scientific agreement, which in turn leads to cascading changes in key beliefs and emotions, which in turn predict support for public action on climate change.

1.2. Public opinion about global warming in China

As attitudes toward global warming vary markedly across countries (Fagan & Huang, 2019; Smith & Mayer, 2019), it remains unclear whether these results generalize to non-WEIRD countries. To our knowledge, no study has yet examined the GBM in a non-WEIRD population. Therefore, the present study will use a national quota sample to conduct a confirmatory replication and extension of the GBM in a non-WEIRD country that is highly influential in the global warming debate, namely China. We propose that China is a particularly interesting case, as it has a strong central government, with only one political party and relatively uniform political views, unlike the United States and Germany (Dang, 2020; Teng & Wang, 2021). This means that the issue of global warming is less politicized in China as it is in representative democracies such as the United States and Germany. Additionally, although the Chinese government actively engages in actions to mitigate global warming and has made ambitious commitments (Wang & Wang, 2017), there is still a lack of research directly investigating the Chinese public's perception of the scientific consensus on human-caused global warming and their attitudes toward related policies. Several studies offer some insights into Chinese public opinion on global warming, but their conclusions differ. Notably, a survey by Većkalov et al. (2024) revealed that the Chinese public underestimated the scientific consensus on anthropogenic climate change, while the China Center for Climate Change Communication (Wang et al., 2017) found that the Chinese public exhibits a high awareness of climate change (see also Liu, 2023). Therefore, the current study will significantly contribute to our understanding of the Chinese population's attitudes toward climate change, especially given China's substantial influence on global climate change mitigation efforts (Engels, 2018; Hurri, 2023; Paltsev, Morris, Cai, Karplus, & Jacoby, 2012; Wang & Wang, 2017). It will also enhance our understanding of the cross-cultural applicability of the GBM.

In addition to focusing on China, the current study makes several methodological improvements as compared to previous studies (Said et al., 2022; van der Linden, 2015, 2019). First, to enhance the robustness of the results (Czerwiński & Atroszko, 2023; Hoeppner, Kelly, Urbanoski, & Slaymaker, 2011), the current study uses multiple items to measure the variables in the GBM, rather than relying on a single item (Said et al., 2022; van der Linden et al., 2015, 2019). Second, in previous studies, researchers have used only general attitudes toward public actions as the dependent variable (Said et al., 2022; van der Linden et al., 2015, 2019). More specific measures of policy support are less strongly associated with global warming beliefs (Hornsey, Harris, Bain, & Fielding, 2016). Thus, to investigate whether consensus messaging also affects support for more specific policies, the current study includes two additional indicators for the dependent variables: support for specific government actions and individual behavioral intentions. Third, previous research suggests that factors such as residence type (rural vs. urban), level of economic development, impact of global warming, and political ideology may influence attitudes toward global warming and support for public actions. Specifically, rural residents tend to face more severe health risks associated with global warming than their urban counterparts (Heaviside, Vardoulakis, & Cai, 2016; Xu et al., 2020). We suggest that such inequality in risks may influence the consensus effect. For example, Hsiang et al. (2017) show that the consequences of climate change are significantly greater for more deprived areas than for richer

areas (see also Tol, 2009, 2018). Thus, we suggest that differences in economic development may also influence how people process the scientific consensus message. Additionally, the effect of the consensus treatment may differ among individuals who experience more severe (vs. less severe) consequences from global warming (Kellstedt, Zahran, & Vedlitz, 2008; Li, Johnson, & Zaval, 2011). Finally, as mentioned earlier, global warming is less politicized in China compared to most Western nations, and therefore less likely to be influenced by political ideology. In summary, the current study will also explore whether these factors influence perceived scientific consensus jointly alongside consensus the treatment. Given that the primary purpose of the current study is to test the GBM in China, these investigations will be treated as exploratory, as outlined in the preregistration.

2. Present study

The primary aim of this study was to conduct a confirmatory replication of the Gateway Belief Model (GBM) proposed by van der Linden et al. (2015, 2019) in a non-WEIRD population, specifically China. This study advances the literature in two key ways. First, to our knowledge, no study has directly replicated the full GBM using the same variables on a high-powered, quota-sampled group of Chinese adults. Second, we extend previous research by enhancing measurement reliability through multi-item measurement of the key beliefs. We also added a series of additional measures, including self-reported impact of global warming, trust in science, and psychological reactance, to evaluate the robustness of the model. Our sample is large and nationally representative in terms of both gender and participants' residential area.[1] Therefore, this study provides a robust test of the GBM in China. This study was preregistered on the Open Science Framework (https://osf.io/jm9hf/?view_only=a43abe8c0eb64fa4a08b8f1a6e14824f) and received formal ethical approval from the relevant institutional review board.

3. Method

3.1. Participants and design

In accordance with Faul, Erdfelder, Buchner, and Lang (2009), we calculated the sample size required for the mixed design using G*power 3.1.9.7. The results suggested that a sample size of 1300 participants would be sufficient to detect an interaction effect of consensus intervention × time point ($f = 0.09$; based on van der Linden, Leiserowitz, & Maibach, 2019) at a significance level (α) of 0.05 and a statistical power (1-β) of 0.90. We obtained a Chinese national quota sample ($N = 1528$) from Credamo, a crowdsourcing platform similar to Amazon Mechanical Turk, between June 6 and June 11, 2024. All participants provided informed consent. In accordance with our preregistered exclusion criteria, nine participants were excluded for being under 18 years of age, and eleven participants were excluded for failing attention check questions (i.e., not selecting option 4 for the item "*Please select option 4 for this question*"). Additionally, the China Statistical Yearbook 2023 provided no gender categories other than male and female. Therefore, two participants who reported their gender as "other" were excluded as they did not meet the gender quota. The analyses indicated that the primary outcomes remained consistent with the inclusion of these participants (see Section 1 in the appendix for details). The final sample included 1506 participants. The sample was nationally representative in terms of both gender and region. The sample approximated the demographics reported in the China Statistical Yearbook 2023. Furthermore, the consensus treatment condition ($n = 755$) and control condition ($n = 751$) were balanced with respect to these characteristics (See Section 2 of the appendix for details).

The experiment employed a mixed factorial design that combined within-participant (post-pre) and between-participant (treatment vs. control) measures. This design is statistically robust, as it controls for sources of within-subject and between-subject variation (Charness, Gneezy, & Kuhn, 2012). Following van der Linden et al. (2015, 2019), participants in the consensus treatment condition were first randomly presented with three blocks of dummy questions (of equal length) on popular media topics to hide the true purpose of the study and reduce potential demand effects. One block contained a question about new regulations on drunk driving in China, another addressed a question about Xiaomi's electric car SU7, and the final block included a question about global warming. They were then (falsely) informed that the researchers possessed a large database of media statements and that they would be randomly presented with one of these statements (the descriptive norm was always the same: "*97% of climate scientists have concluded that human-caused global warming is happening*"). As in van der Linden et al. (2015, 2019), the control group completed a short, neutral word-ordering task. Following the experimental task, participants were asked two questions unrelated to the study's purpose (i.e., about the plot of a classic Chinese TV series) as an additional distraction. Both groups of participants answered the same questions at the beginning (pre-test) and end (post-test) of the survey. These questions covered perceived scientific consensus, beliefs in global warming, beliefs that global warming is human caused, worry about global warming, general attitudes about support for public action, support for specific government actions, and individual behavioral intentions. After the post-test, all participants completed measures about the impact of global warming, political ideology, trust in science, psychological resistance, and demographic variables. Finally, participants received 3 RMB as compensation.

3.2. Measures

Perceived scientific consensus. We measured perceived scientific consensus on a slider scale with three items (e. g., "*To the best of your knowledge, what percentage of climate scientists have concluded that human-caused global warming is happening?*"; pre-test: Cronbach's $\alpha = .82$, McDonald's $\omega = 0.83$; post-test: Cronbach's $\alpha = .88$, McDonald's $\omega = 0.88$), ranging from 0% to 100% (pre-test: $M = 79.81$, $SD = 12.02$; post-test: $M = 84.71$, $SD = 12.17$). The first item in this scale was identical to the one used in van der Linden et al. (2019). Higher scores reflect a greater perception of scientific consensus.

Belief in global warming. Participants were asked to respond on a scale containing three items (e. g., "*How strongly do you believe that global warming is happening*"; pre-test: Cronbach's $\alpha = .59$, McDonald's $\omega = 0.64$; post-test: Cronbach's $\alpha = .53$, McDonald's $\omega = 0.62$). Response options ranged from 1 (*I strongly believe that global warming is not happening*) to 7 (*I strongly believe global warming is happening*), with the following results: pre-test: $M = 6.08$, $SD = 0.76$; post-test: $M = 6.18$, $SD = 0.76$. The first item in this scale was the same as in van der Linden et al. (2019). Higher scores reflect a stronger belief that global warming is happening.

Belief in human-causation. Participants were asked to respond on a scale containing three items (pre-test: Cronbach's $\alpha = .83$, McDonald's $\omega = 0.84$; post-test: Cronbach's $\alpha = .83$, McDonald's $\omega = 0.84$). The first item (i. e., "*How much of climate change do you believe is caused by natural changes in the environment or human activities?*") was consistent with the item used by van der Linden et al. (2019). The next two items (e. g., "*The main causes of global warming are human activities*") were selected from the Climate Change Beliefs Scale used by Ma, Dixon, and Hmielowski (2019). The response options of the first item ranged from 1 (*natural*

[1] We compared the sample characteristics from Credamo with demographic data from the *China Statistical Yearbook* (https://www.stats.gov.cn/sj/ndsj/2023/indexch.htm). Differences were observed between the two in the statistical categories of age, education, and race, which prevented the implementation of quotas for these variables. Additionally, the Yearbook does not provide data on political ideology. Therefore, we applied quotas only for gender and participants' residential area."

changes in the environment) to 7 (*human activities*), while the response options for the last two items ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). The mean of these three scores (pre-test: $M = 5.68$, $SD = 0.83$; post-test: $M = 5.88$, $SD = 0.82$) was used as an indicator of human-caused climate change. Higher scores indicate a stronger belief that climate change is primarily caused by human activities.

Worry about global warming. We measured this variable on a scale with three items (pre-test: Cronbach's $\alpha = .88$, McDonald's $\omega = 0.88$; post-test: Cronbach's $\alpha = .88$, McDonald's $\omega = 0.88$). The first item (i. e., "*How worried are you about global warming?*") was the same with the one used by van der Linden et al. (2019). The next two items (e. g., "*I'm really worried about global warming*") were selected from the Climate Change Beliefs Scale used by Ma et al. (2019). The response options of the first item ranged from 1 (*I am not at all worried about global warming),* 4 (*neutral*), to 7 (*I am very worried about global warming*). Response options for the last two items ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). The mean of these three scores (pre-test: $M = 5.67$, $SD = 0.99$; post-test: $M = 5.77$, $SD = 0.97$) was used as an indicator of worry about global warming. Higher scores indicate greater worry about global warming.

Support *for action on global warming (general attitude)*. We used the same item as van der Linden et al. (2019) to measure general attitudes toward supporting public action to mitigate global warming (i. e., "*Do you think people should be doing more or less to reduce global warming?*"). Responses (pre-test: $M = 6.25$, $SD = 0.92$; post-test: $M = 6.39$, $SD = 0.82$) ranged from 1 (*much less*) to 7 (*much more*). Higher scores indicate stronger support for public action.

Support *for specific governmental actions on global warming*. Similar to Buchanan, Ackland, Lloyd, van der Linden, and de-Wit (2022), we used a scale with three items to measure support for specific government actions. These items described potential government initiatives to foster a more sustainable energy transition, contribute to climate change-related funds, and protect the ecosystem (e.g., "*To drive energy systems away from fossil fuels to reduce greenhouse gas emissions*"; pre-test: Cronbach's $\alpha = .47$, McDonald's $\omega = 0.49$; post-test: Cronbach's $\alpha = .48$, McDonald's $\omega = 0.51$).[2] The scale provided seven response options, ranging from 1 (*very strongly disagree*) to 7 (very strongly agree; pre-test: $M = 5.85$, $SD = 0.63$; post-test: $M = 5.99$, $SD = 0.62$). Higher scores indicate greater support for specific governmental actions on global warming.

Behavioral intentions to act on global warming. We developed a scale with three 7-point Likert items, based on the "Ten Guidelines for Citizens' Ecological and Environmental Behavior" published by the Ministry of Ecology and Environment of China, to measure individuals' behavioral intentions to mitigate global warming (pre-test: $M = 6.24$, $SD = 0.61$; post-test: $M = 6.29$, $SD = 0.60$). These three items focused on resource conservation, green consumption, and waste sorting (e.g., "*Conserving energy resources and reducing daily waste*"; 1 = *very unlikely*, 7 = *very likely*; pre-test: Cronbach's $\alpha = .60$, McDonald's $\omega = 0.60$; post-test: Cronbach's $\alpha = .63$, McDonald's $\omega = 0.63$). Higher scores indicate a stronger willingness to engage in actions aimed at mitigating global warming.

Impact of global warming. To assess participants' perceptions of the personal impact that global warming will have on their health, economic situation, and local environment, we used three adapted items from Kellstedt et al. (2008) ($M = 4.88$, $SD = 1.09$), e.g., "*Global warming and climate change have had and will have a noticeably negative impact on my health*" (Cronbach's $\alpha = .82$, McDonald's $\omega = 0.83$). Responses were measured on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*) and the items were averaged to create an index of personal impact.

Political ideology. We assessed political ideology using a scale developed by Wu (2019), which asked participants to report their views on economic development ($M = 4.53$, $SD = 1.33$; Cronbach's $\alpha = .74$, McDonald's $\omega = 0.76$). Specifically, participants were asked to indicate their agreement with statements such as "*Private ownership of property disadvantages working-class people*" (1 = *strongly disagree*, 7 = *strongly agree*). Higher scores indicate stronger support for left-wing politics in the Chinese context.

Trust in science. Trust in science was measured with a scale consisting of three 7-point items ($M = 5.83$, $SD = 0.58$), e. g., "*How much do you trust science in general*?" (Cronbach's $\alpha = .57$, McDonald's $\omega = 0.62$) (Chinn, Lane, & Hart, 2018). Higher scores represent greater trust in science.

Psychological reactance. Psychological reactance was measured using a scale with three 7-point items (e.g., "*I feel pressure to think a certain way about climate change*"; 1 = *strongly disagree*, 7 = *strongly agree*; $M = 3.72$, $SD = 1.32$, Cronbach's $\alpha = .80$, McDonald's $\omega = 0.81$). The items were taken from an existing scale by Moyer-Gusé and Nabi (2010). Higher scores reflect stronger feelings of being manipulated to form opinions about climate change.

4. Results

4.1. Differences in pre-post test scores on key beliefs and attitudes by consensus treatment

We begin by presenting an overview of the main effects of the consensus treatment (vs. control) on changes (post-pre) in each of the dependent variables. A multivariate MANOVA on the five dependent variables yielded a significant effect, $F\ (7, 1498) = 71.98$, $p < .001$, *Wilk's* $\Lambda = 0.75$. After controlling for gender, subjective social class, annual personal income, and trust in science, the results remained consistent, $F\ (7, 1494) = 72.68$, $p < .001$, *Wilk's* $\Lambda = 0.75$. These variables were controlled for as they were significantly correlated with individual dependent variables in the correlation analysis (see Table 1 for details). Following this, independent samples *t*-tests were conducted on the dependent variables. As hypothesized, there was a large initial effect on perceived scientific consensus ($d = 1.09$), followed by significant effects on the belief in global warming is happening ($d = 0.20$), belief global warming is human-caused ($d = 0.41$), worry about global warming ($d = 0.26$), general attitudes toward increased public action ($d = 0.19$), support for specific governmental actions ($d = 0.48$), and individual behavioral intentions ($d = 0.21$). Results comparing change scores across conditions are provided in Table 2 and visualized in Fig. 2.

4.2. Results of mediation analysis with SEM

We replicated the GBM path relationships with Structural Equation Modelling (SEM), as outlined in van der Linden et al. (2015, 2019), using the same variable and model specifications. All mediation analyses were conducted using maximum likelihood estimation via the *lavaan* package in R 4.3.3 (Rosseel, 2019). Although mediation models are often estimated on observed data (Stone-Romero & Rosopa, 2008), all variables in the model represent pre- and post-differences in beliefs, conditional on experimental assignment, as suggested by van der Linden et al. (2019). This approach strengthens the conclusions regarding causal mediation (Bullock, Green, & Ha, 2010). The main results are visually displayed in Fig. 3, which illustrate the model. The fit indices are as follows: $\chi^2\ (5) = 17.220$, $p = .004$; RMSEA = 0.040, $CI_{90\%}$ [0.021; 0.062]; CFI = 0.982; SRMR = 0.020. These indices suggest an excellent fit according to common criteria (RMSEA <0.08; CFI >0.90; SRMR <0.08; Hopwood & Donnellan, 2010; Hu & Bentler, 1999; West, Taylor, & Wu, 2012). The results also indicate that some of the paths in the model exhibit significant direct effects. A breakdown of all indirect, direct, and total effects

[2] As the reliability was questionable for the variables belief in global warming and support for specific governmental actions, we conducted a series of analyses that provided evidence on model fit, predictive validity, and measurement stability (see Section 3 of Appendix for more details), suggesting that the use of multi-item measures for these variables is superior to single-item measures in this study.

Table 1
Descriptives and correlations.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
1. gender	–	–	–												
2. age	30.84	8.05	0.02	–											
3. SSC	5.20	1.35	−0.05	0.17***	–										
4. Edu	4.96	0.63	−0.06*	−0.19***	0.15***	–									
5. Inc	5.74	2.08	0.04	0.43***	0.34***	0.13***	–								
6. TS	5.83	0.58	0.10***	0.06*	0.13***	0.03	0.12***	–							
7. PR	3.72	1.32	0.04	−0.05	−0.10***	−0.01	−0.15***	−0.15***	–						
8. PSC	4.90	8.97	−0.03	−0.03	−0.06*	0.01	−0.06*	−0.08**	0.04	–					
9. BGW	0.10	0.61	−0.02	−0.00	−0.03	0.02	−0.02	0.04	−0.01	0.20***	–				
10. BHC	0.19	0.45	−0.02	−0.00	−0.04	0.01	−0.04	0.02	0.05	0.29***	0.09***	–			
11. WGW	0.11	0.47	0.10***	−0.04	−0.02	0.03	−0.07**	−0.01	−0.00	0.18***	0.13***	0.09***	–		
12. SAGA	0.14	0.68	0.02	0.03	0.01	0.03	0.01	−0.07**	0.02	0.11***	0.04	0.07**	0.01	–	
13. SSGA	0.08	0.53	−0.08**	0.04	−0.00	0.01	0.01	0.01	0.01	0.22***	0.08**	0.13***	0.10***	0.20***	–
14. BIGW	0.05	0.37	0.03	−0.02	−0.02	0.04	−0.00	0.00	−0.00	0.14***	0.09***	0.13***	0.14***	0.08**	0.07**

Note. $N = 1506$. Gender (1 = Female, 2 = Male); SSC = Subjective Social Class; Edu = Educational Attainment; TS = Trust in Science; PR = Psychological Reactance; PSC = Perceived Scientific Consensus; BGW = Belief in Global Warming; BHC = Belief in Human-Causation; WGW = Worry about Global Warming; SAGA = Support for Public Action on Global Warming (General Attitude); SSGA = Support for Specific Governmental Actions on Global Warming; BIGW = Behavioral Intentions to Act on Global Warming. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

is presented in Tables 3 and 4. Overall, the pattern of results is partially consistent with the model reported by van der Linden et al. (2015, 2019). Experimentally induced changes in perceived scientific consensus significantly predicted pre-post changes in beliefs that global warming is happening, that global warming is human-caused, and worry about global warming. Furthermore, perceived scientific consensus significantly predicted pre-post changes in general support for public actions. However, the current study does not support Stage 2 of the GBM, or the conclusion that changes in these key cognitions and emotion predict greater support for public action. Despite this, perceived scientific consensus had a significant total impact on support for public action.

When examining support for specific government actions as the dependent variable, the results generally align with those obtained for general support for public actions as the dependent variable. The main results are visually displayed in Fig. 4, and the breakdowns of all indirect, direct, and total effects are listed in Tables 5 and 6. Specifically, three key changes were observed. First, consensus treatment had a nonsignificant direct effect ($\beta = 0.104$, 95% CI: −0.007, 0.216, $p = .064$) on general support of public action, but it had a significant direct effect ($\beta = 0.327$, 95% CI: 0.218, 0.437, $p < .001$) on support for specific government actions. The indirect effect of the consensus treatment was not significant when general attitudes toward public actions were used as the dependent variable ($\beta = 0.011$, 95% CI: −0.010, 0.034, $p = .329$). However, this effect became significant when support for specific government actions was the dependent variable ($\beta = 0.027$, 95% CI: 0.007, 0.051, $p = .019$). Furthermore, the consensus treatment had no significant total effect ($\beta = 0.112$, 95% CI: 0.000, 0.227, $p = .052$) on general support of public action, but it had a significant total effect ($\beta = 0.358$, 95% CI: 0.250, 0.470, $p < .001$) on support for specific government actions. Second, the direct effect of belief in global warming being human caused on general attitudes toward public actions was nonsignificant ($\beta = 0.040$, 95% CI: −0.023, 0.104, $p = .207$), but it was significant for support for specific government actions ($\beta = 0.057$, 95% CI: 0.001, 0.116, $p = .050$). Additionally, belief in global warming being human caused had a nonsignificant total effect ($\beta = 0.039$, 95% CI: −0.023, 0.103, $p = .220$) on general support of public action, but it had a significant total effect ($\beta = 0.059$, 95% CI: 0.002, 0.118, $p = .045$) on support for specific government actions. Third, the indirect effect of perceived scientific consensus was not significant when general attitudes toward public action was used as the dependent variable ($\beta = 0.011$, 95% CI: −0.010, 0.033, $p = .339$). However, this effect became significant when support for specific government actions was used as the dependent variable ($\beta = 0.027$, 95% CI: 0.007, 0.050, $p = .016$).

When individual behavioral intentions are used as the dependent variable, the latter part of the mediation model undergoes significant changes compared to when general support for public action is used as the dependent variable. The main results are visually displayed in Fig. 5, and the breakdown of all indirect, direct, and total effects is listed in Tables 7 and 8. Specifically, five key changes were observed. First, the direct effect of belief that global warming is human caused was not significant when general attitudes toward public action were used as the dependent variable ($\beta = 0.040$, 95% CI: −0.023, 0.104, $p = .207$). However, this effect became significant when individual behavioral intentions were used as the dependent variable ($\beta = 0.090$, 95% CI: 0.036, 0.144, $p = .001$). Additionally, the belief that global warming is human caused had a nonsignificant total effect ($\beta = 0.039$, 95% CI: −0.023, 0.103, $p = .220$) on general attitudes in support of public action, but a significant total effect ($\beta = 0.093$, 95% CI: 0.039, 0.149, $p = .001$) on behavioral intentions. Second, the direct effect of worry about global warming was not significant when general attitudes toward public actions were used as the dependent variable ($\beta = -0.033$, 95% CI: −0.096, 0.028, $p = .303$). Yet, this effect became significant when individual behavioral intention was the dependent variable ($\beta = 0.110$, 95% CI: 0.050, 0.170, $p < .001$). Third, the indirect effect of the consensus treatment was not significant when general attitudes toward public

Table 2
The main effect of consensus message on key dependent variables.

Dependent variables	Consensus Treatment Δ Post-Pre (n = 755)		Control Group Δ Post-Pre (n = 751)		t	Cohen's d [95% CI]	BF_{10}
	M	SD	M	SD			
Perceived scientific consensus (0%–100%)	9.17	10.01	0.60	4.87	21.13***	1.09 [0.99, 1.19]	8.37e+82
Belief in global warming (1–7)	0.16	0.69	0.04	0.52	3.82***	0.20 [0.10, 0.30]	76.30
Belief in human-causation (1–7)	0.29	0.50	0.10	0.37	8.04***	0.41 [0.31, 0.52]	2.32e+12
Worry about global warming (1–7)	0.17	0.51	0.05	0.43	5.04***	0.26 [0.16, 0.36]	1.54e+04
Support for public action (1–7)	0.21	0.71	0.08	0.64	3.74***	0.19 [0.09, 0.29]	56
Support for specific governmental actions	0.21	0.44	−0.04	0.59	9.49***	0.48 [0.38, 0.59]	1.76e+17
Individual behavioral intentions (1–7)	0.09	0.39	0.01	0.33	4.02***	0.21 [0.11, 0.31]	165

Note. 0 = control group and 1 = consensus treatment. 95% confidence intervals in parentheses. Cohen's d is a standardized measure of effect size (Cohen, 1988). Bayes factors between 10 and 30 are considered "strong evidence" while values > 30 indicate "very strong evidence" (Kruschke & Liddell, 2018). ***$p < .001$.

action was used as the dependent variable (β = 0.011, 95% CI: −0.010, 0.034, p = .329), but it became significant when individual behavioral intention was the dependent variable (β = 0.046, 95% CI: 0.024, 0.072, $p < .001$). Fourth, perceived scientific consensus had a nonsignificant indirect effect (β = 0.011, 95% CI: −0.010, 0.033, p = .339) on general support of public action, but it had a significant indirect effect (β = 0.046, 95% CI: 0.025, 0.071, $p < .001$) on individual behavioral intentions. Lastly, belief that global warming is happening had a nonsignificant indirect effect (β = −0.003, 95% CI: −0.011, 0.003, p = .346) on general support of public action but a significant indirect effect (β = 0.011, 95% CI: 0.003, 0.021, p = .028) on individual behavioral intentions. Additionally, belief that global warming is happening had a nonsignificant total effect (β = 0.020, 95% CI: −0.034, 0.075, p = .468) on general attitudes in support of public action but a significant total effect (β = 0.061, 95% CI: 0.008, 0.116, p = .025) on behavioral intentions.

Even with the inclusion of control variables such as gender, subjective social class, income, and trust in science, the results of mediation analysis with SEM remain largely consistent (see Section 5 of the appendix for details).

4.3. Between-participants ANOVA on the post-pre difference of key cognitions and emotions

We further examined the main effects of long-term residence (rural vs. urban), type of household registration (agricultural vs. non-agricultural), regions based on GDP growth rate (eastern vs. central vs. western vs. northeastern), perceived impact of global warming, and political ideology (preference for a market economy vs. preference for government intervention) on perceived scientific consensus, as well as their respective interactions with the consensus treatment. A between-participants ANOVA on post-pre scores revealed the following findings. First, the main effect of the experimental treatment on perceived scientific consensus was significant in all situations, Fs > 444.33, ps < 0.001. Second, the perceived impact of global warming had a main effect on perceived scientific consensus, F (1, 1502) = 4.94, MSE = 304, p = .026, η^2 = 0.003. Furthermore, there was a significant interaction effect with the consensus treatment, F (1, 1502) = 8.74, MSE = 539, p = .003, η^2 = 0.005 (as shown in Fig. 6). Third, the main effects of long-term residence, household registration, regions based on GDP growth rate, and political ideology were not significant (ps > 0.193), nor were any of their interactions with the consensus treatment (ps > 0.166). It is noteworthy that this interaction did not reliably emerge in any of the other key cognitions and emotion (ps > 0.05), see Section 4 of the appendix for details.

We then used the Tukey HSD test to conduct pairwise comparisons of the means of perceived scientific consensus across different conditions. In the consensus treatment condition, only participants who were less strongly impacted by global warming exhibited a greater change in perceived scientific consensus than those who were more strongly impacted by global warming (t = 2.36, p = .021, Cohen's d = −0.24, 95%CI: −0.41, −0.06).

5. Discussion

In recent years, there has been rapid growth in the scholarly literature on the application of the Gateway Belief Model (GBM) to the field of climate change (Bayes et al., 2023; van der Linden, 2021). Some researchers have replicated this model, but many studies were limited by sampling exclusively from WEIRD populations using single-item measures. In the current study, we conducted a conceptual confirmatory replication of the GBM using a national quota sample from China with multi-item measurements. We also tested the influence of factors such as impact of global warming on the effect of the consensus message. The results showed that the consensus message significantly increased people's perception of the scientific consensus. It also increased beliefs that global warming is happening, that it is human-caused, and heightened worry about global warming. Additionally, perceived scientific consensus directly influenced support for public actions, even when controlling for other key cognitions and emotions.

5.1. Contributions

The present study makes several specific contributions. First, to the best of our knowledge, it is the first large-scale replication study of the GBM in a non-WEIRD population. Previous GBM replication studies have primarily come from countries such as the United States and Germany (e.g., Lewandowsky et al., 2013; Said et al., 2022; van der Linden et al., 2019). The current study drew on a national quota sample from China, a society markedly different from the United States and Germany given its strong central government and political environment characterized by relatively unified political views (Dang, 2020; Teng & Wang, 2021). The issue of global warming is therefore less politicized and less subject to persistent conflicts in China (Heath & Gifford, 2006; Lewandowsky et al., 2013; van der Linden et al., 2019; Zhang et al., 2018). The results of the current study illuminate the implications of these differences. In China, political ideology does not predict changes in perceived scientific consensus, nor does it influence the increase in perceived scientific consensus through consensus messaging. Thus, the current study extends the research on the effects of communicating scientific consensus to societies with larger populations and a different political system, providing valuable evidence for understanding the manifestation of the GBM in non-WEIRD populations.

It is important to note that the main effects of the experimental treatments in these findings may be considered small by general standards (Cohen, 1988). However, the effect sizes in the current study should not necessarily be regarded as trivial. Researchers have argued that effect sizes should be interpreted in relative, rather than absolute, terms (Carey et al., 2023; Funder & Ozer, 2019; Gelman & Carlin, 2014; Primbs et al., 2023). Specifically, effect sizes should be understood in context. Compared to the broader literature on persuasion effects (Weber & Popova, 2012), the five effect sizes observed in this study fall between at least the 50th and 75th percentiles. Notably, the experimental treatment effects on perceived scientific consensus, worry about global warming, and support for specific governmental actions rank

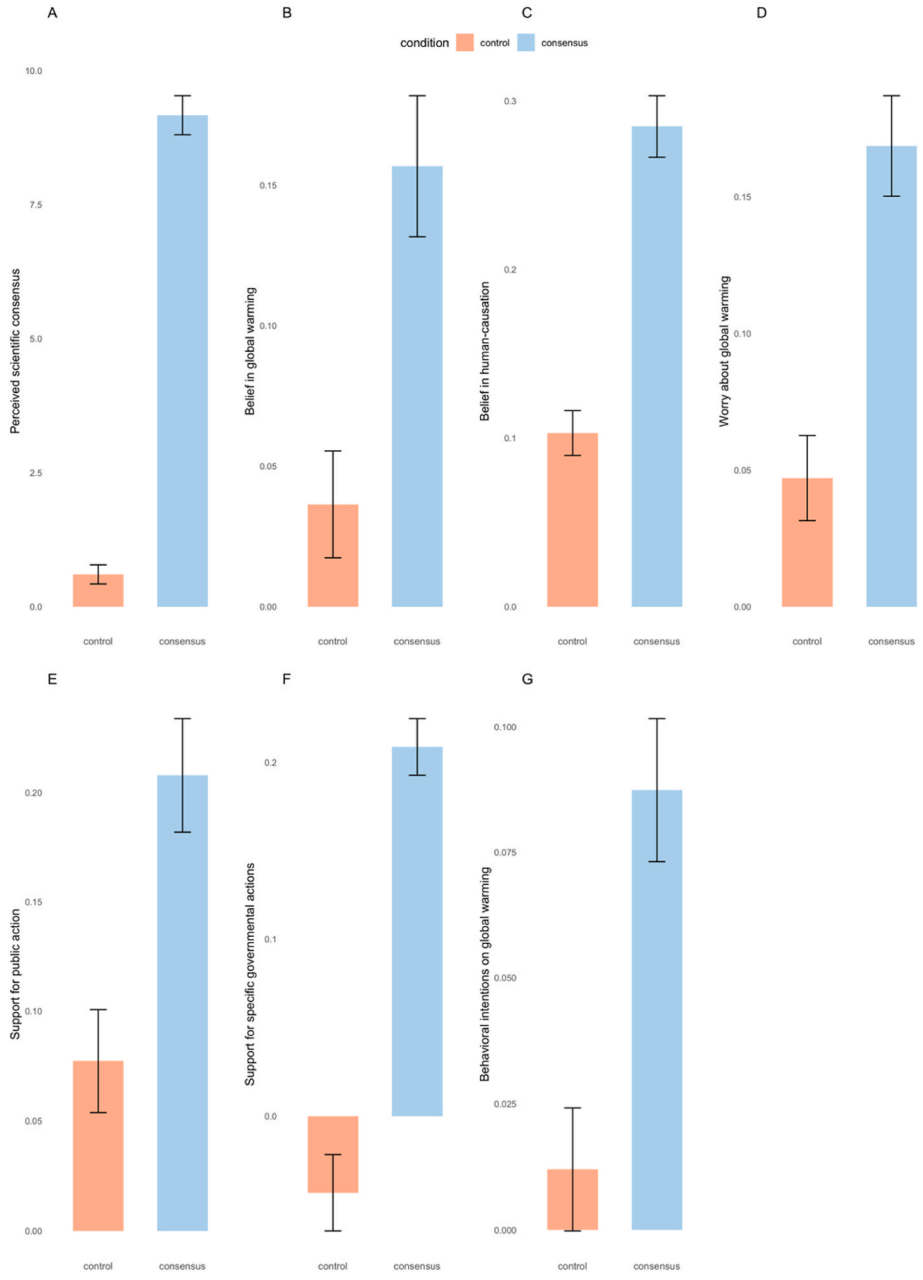


Fig. 2. Main effect (post-pre) on perceived scientific consensus

Note. $N = 1506$. Main effects (post-pre) by experimental condition for the following dependent variables: perceived scientific consensus (panel A), belief in global warming is happening (panel B), belief in global warming is human caused (panel C), worry about global warming (panel D), general attitudes in support of public action (panel E), support for specific governmental action (panel F), and individual behavioral intentions (panel G).

between the 75th and 90th percentiles. As van der Linden et al. (2019) suggested, this is particularly impressive given that the experimental manipulation solely emphasized scientific consensus without directly targeting cognitions, emotions, or actions. Furthermore, small effects can still hold substantial importance, especially when experimental manipulations are minimal and the dependent variable is challenging to influence (Prentice & Miller, 1992). Our study satisfies both of these conditions: the manipulation consisted of a simple statement reflecting scientific consensus, and public perceptions and actions related to climate change are well-documented as difficult to change (Gifford, 2011). For an issue as critical as climate change, which affects humanity on a global scale, even small effects can be important when scaled at population level (Anvari et al., 2023; Kahan & Braman, 2003; Durkin, Brennan, & Wakefield, 2012). For example, as van der Linden et al. (2019) pointed out, "*a d of 0.15 roughly translates to a change in public* support *from 50% to 54%—recent referenda and elections have hinged on less (e.g., Brexit 51.9% vs. 48.1%).*" Lastly, small effects can have long-term implications when viewed through a temporal lens (Abelson, 1985; Anvari et al., 2023; Götz, Gosling, & Rentfrow, 2022). As cultural norms evolve, attitudes and behaviors often shift (Gergen, 1973). Recent evidence has shown that public perceptions of the scientific consensus, along with the belief that climate change is human-caused, have increased since 2010, while polarization surrounding these beliefs has decreased (Ballew et al., 2024; Cook et al., 2018; Hamilton, 2016;

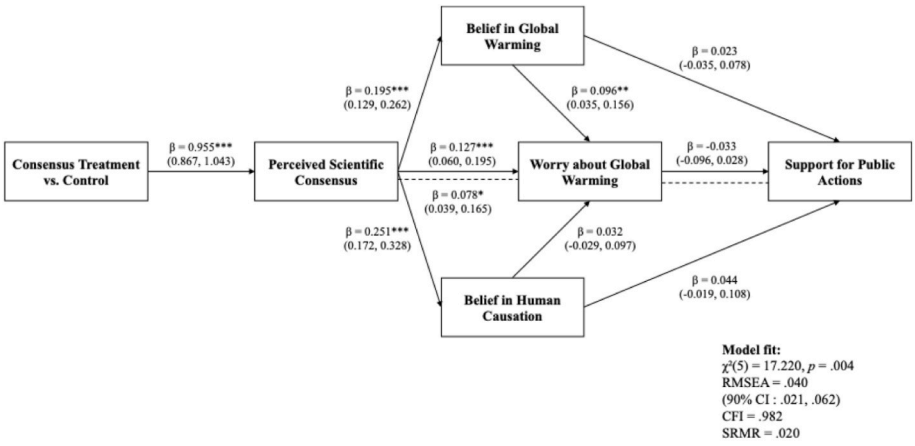


Fig. 3. Gateway Belief Model (GBM)
Note. $N = 1506$. Coefficients are standardized and 95% confidence intervals are provided in parentheses. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 3
SEM model parameters (direct effects).

Model path relationships	β	95% CI	*p*
Condition → PSC	0.955	0.867, 1.043	<0.001***
Condition → BGW	0.009	−0.109, 0.123	0.874
Condition → BHC	0.166	0.060, 0.278	0.003**
Condition → WGW	0.104	−0.009, 0.218	0.068
Condition → SAGA	0.104	−0.007, 0.216	0.064
PSC → BGW	0.195	0.129, 0.262	<0.001***
PSC → BHC	0.251	0.172, 0.328	<0.001***
PSC → WGW	0.127	0.060, 0.195	<0.001***
BGW → WGW	0.096	0.035, 0.156	0.002**
BHC → WGW	0.032	−0.029, 0.097	0.329
BGW → SAGA	0.024	−0.032, 0.079	0.407
BHC → SAGA	0.040	−0.023, 0.104	0.207
WGW → SAGA	−0.033	−0.096, 0.028	0.303
PSC → SAGA	0.078	0.011, 0.149	0.026*

Note. $N = 1506$. PSC = Perceived Scientific Consensus; BGW = Belief in Global Warming; BHC = Belief in Human-Causation; WGW = Worry about Global Warming; SAGA = Support for Public Action on Global Warming (General Attitude). *$p < .05$. **$p < .01$. ***$p < .001$.

Leiserowitz et al., 2024; Leiserowiz et al., 2023).

Second, we found intriguing new results regarding the interaction between the effects of global warming and the consensus treatment. Specifically, the consensus treatment significantly increased the perception of scientific consensus compared to the control group, regardless of the degree of exposure to global warming (as shown in Fig. 2). However, individuals less affected by global warming experienced the greatest change in perceiving scientific consensus in the consensus treatment condition. We suggest that this may be because individuals less impacted by global warming are most likely to underestimate the scientific consensus on global warming prior to participating in the experiment. Thus, the consensus treatment triggered a stronger perception of changes in scientific consensus for them. The data in this paper support these accounts (*ps* < 0.001; see Appendix, Section 6 for details). Taken together, these findings emphasize the critical role of consensus treatments in enhancing public perceptions of the scientific consensus on global warming, especially among populations less affected by global warming. It is important to recognize that, in addition to partisan and ideological factors (Cook, Lewandowsky, & Ecker, 2017; Kahan, Jenkins-Smith, & Braman, 2011; Lewandowsky et al., 2013; van der Linden et al., 2019), the effects of communicating scientific consensus are influenced by more specific (experiential) factors.

Third, the current study found that the consensus treatment not only predicts support for public actions consistent with van der Linden et al. (2019), butalso extends to more specific government actions and individual behavioral intentions by increasing perceived scientific consensus. This is a novel finding compared to previous studies (Said et al., 2022; van der Linden et al., 2019). Notably, these results come from a scale containing multiple items, overcoming the limitations of previous replication studies that used single-item measures (Czerwiński & Atroszko, 2023; Hoeppner et al., 2011). In addition, changes in key beliefs arising from an increase in perceived scientific consensus elevated individual behavioral intentions, even though they did not predict attitudes toward public action and support for specific governmental actions, a significant deviation from prior work (see van der Linden, 2021). One cross-cultural explanation may be rooted in China's strong central government, which tends to promote top-down public policies, such as global warming mitigation (Dang, 2020; Teng & Wang, 2021).

Specifically, due to economic transformation and other factors (Barbi, Ferreira, & Guo, 2016; Liu, Wang, & Wu, 2017; Tsang & Kolk, 2010; Wang, Liu, & Wu, 2018), China's top-down leadership has issued directives to promote the development of an ecological civilization. Subsequently, the central government designates specific policies and cascades them down to lower levels of government for implementation.

Table 4
SEM model parameters (indirect and total effects).

Model path relationships	$\beta_{indirect}$	95% CI	*p*	β_{total}	95% CI	*p*
Condition → BGW	0.187	0.122, 0.256	<0.001***	0.196	0.094, 0.295	<0.001***
Condition → BHC	0.240	0.162, 0.320	<0.001***	0.406	0.308, 0.503	<0.001***
Condition → WGW	0.122	0.056, 0.188	<0.001***	0.253	0.153, 0.352	<0.001***
Condition → SAGA	0.011	−0.010, 0.034	0.329	0.112	0.000, 0.227	0.052
PSC → SAGA	0.011	−0.010, 0.033	0.339	0.089	0.025, 0.156	0.007**
BGW → SAGA	−0.003	−0.011, 0.003	0.346	0.020	−0.034, 0.075	0.468
BHC → SAGA	−0.001	−0.006, 0.003	0.561	0.039	−0.023, 0.103	0.220

Note. $N = 1506$. PSC = Perceived Scientific Consensus; BGW = Belief in Global Warming; BHC = Belief in Human-Causation; WGW = Worry about Global Warming; SAGA = Support for Public Action on Global Warming (General Attitude). Indirect effects ran through multiple mediators. **$p < .01$. ***$p < .001$.

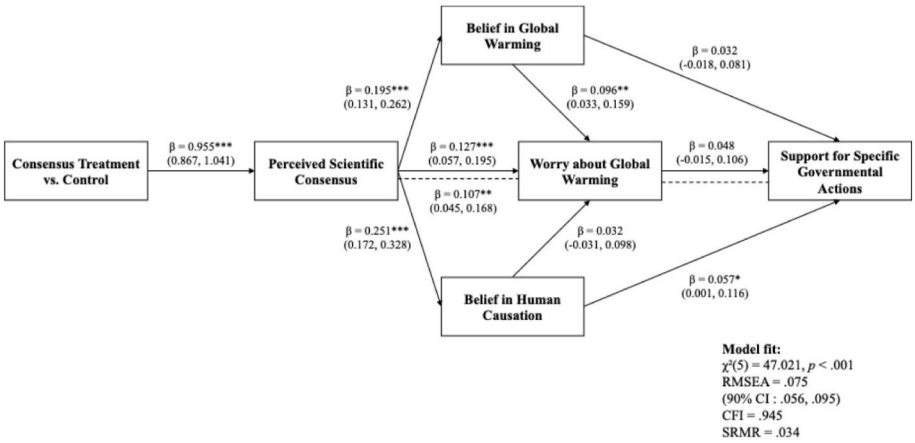


Fig. 4. Gateway Belief Model (GBM)
Note. $N = 1506$. Coefficients are standardized and 95% confidence intervals are provided in parentheses. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 5
SEM model parameters (direct effects).

Model path relationships	β	95% CI	*p*
Condition → PSC	0.955	0.867, 1.041	<0.001***
Condition → BGW	0.009	−0.104, 0.126	0.872
Condition → BHC	0.166	0.058, 0.278	0.003**
Condition → WGW	0.104	−0.008, 0.218	0.071
Condition → SSGA	0.327	0.218, 0.437	<0.001***
PSC → BGW	0.195	0.131, 0.262	<0.001***
PSC → BHC	0.251	0.172, 0.328	<0.001***
PSC → WGW	0.127	0.057, 0.195	<0.001***
BGW → WGW	0.096	0.033, 0.159	0.002**
BHC → WGW	0.032	−0.031, 0.098	0.339
BGW → SSGA	0.032	−0.018, 0.081	0.199
BHC → SSGA	0.057	0.001, 0.116	0.050*
WGW → SSGA	0.048	−0.015, 0.106	0.125
PSC → SSGA	0.107	0.045, 0.168	0.001**

Note. $N = 1506$. PSC = Perceived Scientific Consensus; BGW = Belief in Global Warming; BHC = Belief in Human-Causation; WGW = Worry about Global Warming; SAGA = Support for Specific Governmental Actions on Global Warming. *$p < .05$. **$p < .01$. ***$p < .001$.

The success of these policies is then used as a reference standard for the performance appraisal of lower-level government officials. Although public opinion can be somewhat responsive to these public affairs (Kornreich, 2019; Meng, Pan, & Yang, 2017), bottom-up pressures still have limited influence on policymaking (Chen, 2017; Huang & Kim, 2020). According to this pattern of decision-making, Chinese populations may be less inclined to participate actively in public decision-making (Huang, Castán Broto, & Westman, 2020; Yang, Hwang, & Mattila, 2021) and may possess a lower sense of efficacy (Burnham & Ma, 2017). Thus, the effect of the consensus treatment on perceived scientific consensus, as well as on subsequent cognitions and emotions, did not translate into increased support for public action, in terms of general attitudes or specific government actions. However, it is noteworthy that the consensus treatment did promote behavioral intentions to engage in global warming mitigation. These results align with the first contribution and highlight the importance of replication studies in diverse populations (Bayes et al., 2023; Liu, 2023; van der Linden, 2021; van der Linden et al., 2019).

5.2. Limitation and future research

The current study has some limitations. First, the low scale reliability of the scale for support for specific government actions may raise doubts about the relevant results. And previous studies have found that the more specific the measure of policy support the less likely it is to be associated with attitudes toward climate change (Hornsey et al., 2016; Bayes et al., 2023; Levine & Kline, 2019). However, in this study, the GBM model using multiple-item measures for support for specific government actions as the dependent variable demonstrated good fit, yielding more stable results and larger effects overall compared to single-item measures (see Section 3 of Appendix for details). Despite this, we acknowledge the limitations posed by the low reliability of the scales employed in this study. To better understand the relationship between consensus messaging and specific policy support, we encourage future researchers to develop multidimensional scales with higher reliability (e.g., addressing dimensions such as policy advocacy, financial investment, and green consumption) to assess attitudes toward these actions. Additionally, testing each dimension individually in relation to other variables while maintaining predictive validity and measurement stability could provide valuable insights.

Second, the current study replicated the GBM in a sample from China, representing a non-WEIRD population, but we did not compare it to a WEIRD sample. This limitation prevents us from determining whether the effect of the consensus treatment differed significantly across non-WEIRD and WEIRD populations. Additionally, it is not

Table 6
SEM model parameters (indirect and total effects).

Model path relationships	$\beta_{indirect}$	95% CI	*p*	β_{total}	95% CI	*p*
Condition → BGW	0.187	0.123, 0.255	<0.001***	0.196	0.097, 0.295	<0.001***
Condition → BHC	0.240	0.161, 0.318	<0.001***	0.406	0.307, 0.508	<0.001***
Condition → WGW	0.122	0.055, 0.187	0.009**	0.253	0.153, 0.352	<0.001***
Condition → SSGA	0.027	0.007, 0.051	0.019*	0.358	0.250, 0.470	<0.001***
PSC → SSGA	0.027	0.007, 0.050	0.016*	0.134	0.073, 0.195	<0.001***
BGW → SSGA	0.005	−0.001, 0.013	0.208	0.037	−0.014, 0.087	0.147
BHC → SSGA	0.001	−0.002, 0.007	0.488	0.059	0.002, 0.118	0.045*

Note. $N = 1506$. PSC = Perceived Scientific Consensus; BGW = Belief in Global Warming; BHC = Belief in Human-Causation; WGW = Worry about Global Warming; SAGA = Support for Specific Governmental Actions on Global Warming. Indirect effects ran through multiple mediators. *$p < .05$. ***$p < .001$.

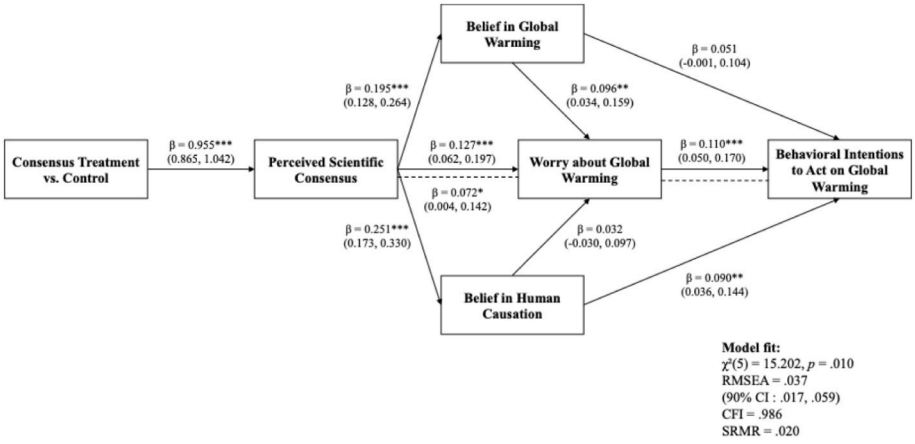


Fig. 5. Gateway Belief Model (GBM)
Note. $N = 1506$. Coefficients are standardized and 95% confidence intervals are provided in parentheses. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 7
SEM model parameters (direct effects).

Model path relationships	β	95% CI	*p*
Condition → PSC	0.955	0.865, 1.042	<0.001***
Condition → BGW	0.009	−0.107, 0.123	0.873
Condition → BHC	0.166	0.056, 0.277	0.003**
Condition → WGW	0.104	−0.007, 0.022	0.070
Condition → BIGW	0.062	−0.060, 0.179	0.307
PSC → BGW	0.195	0.128, 0.264	<0.001***
PSC → BHC	0.251	0.173, 0.330	<0.001***
PSC → WGW	0.127	0.062, 0.197	<0.001***
BGW → WGW	0.096	0.034, 0.159	0.002**
BHC → WGW	0.032	−0.030, 0.097	0.334
BGW → BIGW	0.051	−0.001, 0.104	0.057
BHC → BIGW	0.090	0.036, 0.144	0.001**
WGW → BIGW	0.110	0.050, 0.170	<0.001***
PSC → BIGW	0.072	0.004, 0.142	0.043*

Note. $N = 1506$. PSC = Perceived Scientific Consensus; BGW = Belief in Global Warming; BHC = Belief in Human-Causation; WGW = Worry about Global Warming; BIGW = Behavioral Intentions to Act on Global Warming. *$p < .05$. **$p < .01$. ***$p < .001$.

possible to assess how the GBM performs across different samples within the same study. To date, no study has provided this information. Therefore, we encourage future research to conduct larger global surveys that encompass populations from more diverse societies (i.e., not limited to the dichotomy between non-WEIRD and WEIRD; Apicella, Norenzayan, & Henrich, 2020; Ghai, 2021; Muthukrishna et al., 2020) to more fully investigate the applicability of the GBM across different cultural contexts.

Third, the design of the current study limits our ability to assess the persistence of consensus treatment effects. Although several longitudinal studies have investigated the long-term effects of consensus beliefs, their findings have been inconsistent (Deryugina & Shurchkov, 2016; Goldberg et al., 2022; Kerr & Wilson, 2018; Maertens, Anseel, & van der Linden, 2020; van der Linden et al., 2018). Thus, future research on the effects of consensus treatments over a prolonged time would be beneficial. Additionally, the effect of beliefs on dependent variables (2nd stage) is perhaps not purely causal. We encourage future researchers to employ experimental causal chain designs (Spencer, Zanna, & Fong, 2005; van der Linden, 2021) to examine the causality of second-order mediating effects within the model.

Finally, our sample is nationally representative only in terms of gender and place of residence. However, the participants' education levels, annual personal incomes, and subjective social class means all exceed the scale median (see Table 1 for details). This suggests that our participants were more likely to be social elites with higher education and income. Previous studies have shown that disadvantaged groups in society are particularly vulnerable to global warming compared to elites (Hsiang et al., 2017; Watts et al., 2018). Despite being the majority in society, the effects of consensus messaging among these disadvantaged groups remain poorly understood (Ballew, Pearson, Goldberg, Rosenthal, & Leiserowitz, 2020; Bayes et al., 2023). Therefore, although these variables did not significantly affect the results of the current study, we still encourage future research to include more disadvantaged segments of society.

6. Conclusions

The current study directly replicated the Gateway Belief Model in a Chinese national quota sample. The results suggest that exposure to scientific consensus information significantly increases people's understanding of the scientific consensus on climate change, which in turn induces changes in their cognitions and emotions related to climate change. Furthermore, for those less impacted by climate change, exposure to the consensus message led to greater increases in perceived scientific consensus. These findings enhance our understanding of the

Table 8
SEM model parameters (indirect and total effects).

Model path relationships	$\beta_{indirect}$	95% CI	*p*	β_{total}	95% CI	*p*
Condition → BGW	0.187	0.120, 0.255	<0.001***	0.196	0.095, 0.293	<0.001***
Condition → BHC	0.240	0.161, 0.321	<0.001***	0.406	0.309, 0.503	<0.001***
Condition → WGW	0.122	0.059, 0.190	<0.001***	0.253	0.153, 0.356	<0.001***
Condition → BIGW	0.046	0.024, 0.072	<0.001***	0.120	−0.004, 0.238	0.052
PSC → BIGW	0.046	0.025, 0.071	<0.001***	0.119	0.051, 0.189	0.001**
BGW → BIGW	0.011	0.003, 0.021	0.028*	0.061	0.008, 0.116	0.025*
BHC → BIGW	0.003	−0.003, 0.012	0.368	0.093	0.039, 0.149	0.001**

Note. $N = 1506$. PSC = Perceived Scientific Consensus; BGW = Belief in Global Warming; BHC = Belief in Human-Causation; WGW = Worry about Global Warming; BIGW = Behavioral Intentions to Act on Global Warming. Indirect effects ran through multiple mediators. *$p < .05$. **$p < .01$. ***$p < .001$.

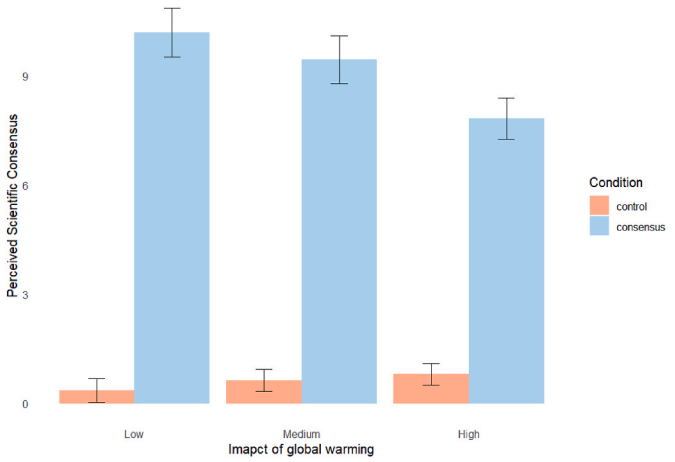


Fig. 6. Scientific Consensus Across IGW Levels and Conditions
Note. $N = 1506$. We categorized the 7-point Likert-score impact of global warming scale into high, medium, and low levels. Each observation is an integer between 1 (lowest level) and 7 (highest level). This categorization method does not alter the original impact of global warming observations.

applicability of the Gateway Belief Model in non-WEIRD countries, highlighting the role of raising awareness of the scientific consensus in China as a gateway to supporting climate action. They also provide insights for advancing climate change science communication and policymaking, particularly for engaging those less directly affected by global warming.

CRediT authorship contribution statement

Zhao-Xie Zeng: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jan-Willem van Prooijen:** Writing – review & editing, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Yong-Yu Guo:** Writing – review & editing, Resources, Funding acquisition. **Sander van der Linden:** Writing – review & editing, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Ethical approval and informed consent statements

This study was approved by the ethics committee of Vrije Universiteit Amsterdam (approval no. VCWE-S-21-00228). Participants gave informed consent.

Data availability statement

The data that support the findings of this study are openly available on the Open Science Framework at https://osf.io/6e4v3/?view_only=26cd07a3899f41219b546a20c3de23ec.

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Declaration of conflicting interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvp.2025.102542.

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