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Global Warming, Nationalism, and Reasoning With Numbers: Toward Techniques to Promote the Public's Critical Thinking About Statistics

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Abstract

The increase of misinformation in the public sphere over the past decade represents an urgent societal issue, given the challenge of distinguishing veridical facts from false or misleading information. The present experiment's results indicate that people are reliant on numerical information in their determination of whether a statistic related to global warming is representative or misleading. Of particularly practical significance, the results also demonstrate that showing participants a mixed set of revealing and misleading global warming statistics leads to an increase in global warming acceptance, rather than sowing confusion (or some sense that all data are equally dubious or compelling). Replicating prior results, nationalism and global warming acceptance are in a negative relationship. We also describe the background, design, and assessment of a curriculum intended to help the general public better distinguish between representative and misleading statistics about anthropogenic climate change. The findings highlight numerically-driven inferencing as a useful paradigm for the assessment of information relating to global warming and environmental risk.

Keywords: global warming; climate change; representativeness; misinformation; misleading information; numerical cognition; nationalism; statistical interpretation.

Introduction

The increasing use of facts and figures in 21st-century public life is a double-edged sword. For example, consider testing for SARS-CoV-2. At "press time" for this piece (late May, 2020), the U.S. leads all nations in conducted tests for COVID-19, which might initially imply safety for its residents; however, this offers little true solace, given that the U.S. (with only 4% of Earth's human population) also leads the world in confirmed cases and deaths suffered—by factors of nearly five and three compared to the next-most coronavirus-suffering respective nations. (Antarctica is the continent with the least tests, having zero cases just now.)

Accurate numbers and statistics can ground statements in a much-needed objective reality, but the implied authority of numeric entities can be exploited. Misinformation about global warming (GW) in the public realm, and misleading assertions such as the claim that over 30,000 "scientists" (many now deceased) have declared GW a hoax (van der Linden et al., 2017), can easily be encoded by the more naive as "fact" (as Johnson & Seifert, 1994, noted with other content)—even when people have adequate knowledge and awareness that what they are learning is incorrect (Fazio et al., 2013) or that the information-source may be deceptive (Green & Donahue, 2011). It has similarly been shown that exposing even well-educated people to misleading, cherry-picked statistics (e.g., that Earth cooled a tiny 0.2°F during 1940-1975) reduces participants' (a) recognition that climate-change is occurring (i.e., GW acceptance), (b) climate-change funding preferences, and (c) self-ratings of global warming knowledge (Ranney & Clark, 2016; Ranney Shonman, Fricke, Lamprey, & Kumar, 2019). With even digitally savvy college students being unable to differentiate between a real news story and a fake piece of sponsored content (Wineburg & McGrew, 2016), both the public and journalists have a growing need for tools to properly diagnose auditory/visual materials to become *informed* (as opposed to, e.g., blanket) skeptics (Ranney et al., 2008; Yarnall & Ranney, 2017).

Study Motivations

Our motivations were initiated by phenomena from Ranney and Clark (2016: Experiments 6-7), which were replicated by Ranney et al. (2019; Experiments 2 and 4): These experiments demonstrated that exposing participants to a set of representative (i.e., salient/diagnostic) statistics (see Table 1) related to global warming increased their climate change acceptance, whereas exposing participants to a set of misleading GW statistics (i.e., technically true but cherry-picked data typically used by fossil-fuel lobbyists hoping to foster climate change denial) resulted in a significant decreases in global warming acceptance.

In contrast to the experimental domain, however, people are often exposed to a mix of misleading and representative information from various sources and contexts. Given this, we hypothesized about the effects of a *mixed* set of misleading-plus-representative GW statistics (i.e., representative and misleading statistics interspersed) on GW acceptance—a setup more ecologically reflecting the reality that misleading and representative information are often encountered in close proximity in everyday life. To help ensure that it would be the *participants'* identification of the representativeness/misleadingness of each statistic causing a change in global warming acceptance, we designed an intervention to help participants to better identify salient features of representative or misleading statistics—and thus to help them better differentiate between the two.

Table 1: Some salient statistics about global warming (from Ranney & Clark, 2016) included in this experiment.

A 2010 article examined the 908 active researchers with at least 20 climate publications on Google Scholar. **97.5** % of them have stated that it is "very likely" that human-caused emissions are responsible for "most" of the "unequivocal" warming of the Earth in the second half of the 20th century.
Global surface temperatures have been recorded since 1880. According to the U.S. government's National Climatic Data Center, **19** of the 20 years between 1995-2014 were each one of the hottest 20 years ever recorded.
According to the U.S. Geological Survey, there were approximately 150 glaciers present in the Glacier National Park in 1850. **25** glaciers are present today.
From 1850 to 2013, the volume of glaciers in the European Alps decreased by **65** %.
According to the Intergovernmental Panel on Climate Change, atmospheric levels of methane (a greenhouse gas) have increased by **151**% since 1750.
According to the National Climatic Data Center, of the last 374 months, **374** have been above Earth's 20th-century average monthly temperature.
The federal National Oceanic and Atmospheric Administration (NOAA) observes temperatures at almost 2000 U.S. locations. According to a published 2009 study using 9 years of NOAA data, for every 100 record temperature lows recorded, **204** record temperature highs were recorded in the United States.

We also theorized about how one's numeracy and estimation skills might intersect with one's ability to distinguish between revealing/misleading statistics. Prior work has shown that Numerically-Driven Inferencing (NDI) techniques—for instance, estimating unknown quantities related to important policy issues before receiving the true values as feedback—fosters critical thinking and belief revision (Ranney, Cheng, Garcia de Osuna, & Nelson, 2001; Ranney, Munnich, & Lamprey, 2016; Munnich & Ranney, 2019). A mechanism for such belief revision has been suggested to arise from a network of hypotheses, evidence, set relationships, and causal beliefs (cf. Ranney & Thagard, 1988; Thagard, 1989) that are activated during the act of estimating. Using a variation on the "EPIC procedure" (e.g., Munnich, Ranney, & Appel, 2004), the mixed set of representative and misleading statistics about GW were modified such that versions of each item were available with and without the key numerical part of the statistic present. The item-type without the number used blanks and are referred to as "blank-first" items because participants eventually received the item with the blank filled in as kind of numeric feedback. Here is a misleading item (mentioned in the Introduction) changed from its "regular" incarnation to a "blank-first" incarnation:

According to the National Oceanic and Atmospheric Administration, the average global temperature changed by ____ degrees F between 1940 and 1975.

Methods

The Development of the Curricular Intervention

We developed a short, self-contained curriculum (intervention) that identifies for the reader four main aspects of a statistic that, alone or together, could largely deem whether any statistic is revealing, pointless, or non-passively (e.g., intentionally) misleading. The curriculum's content was a modified and shortened adaptation of a one-week mini-course providing quantitative/reasoning skills to M.A. journalism students at the University of California, Berkeley; the mini-course showed solid delayed-posttest gains even after nine weeks (Ranney et al., 2008), and included a medley of exercises and sampled sources, including excellent/poor newswriting exemplars, and portions of both current and classic texts such as *How to Lie with Statistics* (Huff, 2010). The new curriculum also changed the 2008 mini-course version by adapting more recent research on rhetorical tools and devices that have commonly been used in association with misleading information, (e.g., new findings about cherry-picking phenomena; Lewandowsky & Oberauer, 2016, etc.).

In brief, participants were encouraged to be sensitive to 1) the *four-dimensional breadth* of the statistic (i.e., whether a presented quantity covered a representatively large extent over time and space/population, as appropriate), 2) *numerical error*, 3) *possible source bias*, and 4) *misleadingness* (i.e., whether a measure being considered was relatively inappropriate for inciting reasonable inferences/conclusions). Pilot studies showed that the distinction between a pointless and a misleading statistic was nontrivial for participants to grasp, so we added several contrastive examples to the curricular materials. After providing a brief description of each of these distinction criteria, we also presented a sample statistic that Chris, "a family friend," had offered in support of a claim. Following this, we asked each participant exposed to the curriculum to describe in what ways an example statistic might be revealing or misleading. The curriculum concluded with practice statistics, and participants were asked to rate the statistics' misleadingness/revealingness using a -4 to +4 scale, both without (using a blank; see above) and with the number present. (Participants also estimated, on a 0-100 scale, how much of the curriculum they read; if their estimate was below 70%, we used this as one of several participant-exclusion criteria—e.g., with attention checks.)

Overview of Study Conditions

The prepared set of mixed representative and misleading statistics described in the section above, in both their blank-first and regular incarnations (e.g., blank-first and regular items) comprised our pre/post-test, along with a list of "RTMD" (e.g., Ranney, Clark, Reinholz, & Cohen, 2012;

Ranney et al., 2019) items to assess self-ratings (on a 1-9 scale) of, among other constructs, participants' GW acceptance, level of nationalism and level of acceptance of biological evolution. (RTMD is "Reinforced Theistic Manifest Destiny" theory; Ranney, 2012.) The motivation to measure changes in these constructs was due to the fact that prior work has shown that global warming resides at a crux of many societally contentious issues involving science, religion, and identity—particularly in the US: for instance, Ranney et al. (2019) showed that one's GW acceptance has a crucially bi-causal relationship with nationalism, such that (a) decreasing one's sense of nationalism increases one's acceptance of GW's reality (also Luong, 2015) and (b) increasing one's acceptance of GW's reality decreases one's sense of nationalism (as Velautham & Ranney, 2019, also found). Participants were additionally asked three extra questions about the mechanism of global warming to assess the GW knowledge of participants and a question about how many dollars (out of $1000) they would donate to a global warming charity (vs. their favorite), to provide an additional metric of participants' global warming acceptance.

Four kinds of conditions were employed: (i) a control condition (simply exposing participants to the statistics and assessing their GW acceptance, before and after), (ii) a sandwich condition that included a pre-test (the complete set of mixed statistics, as well as RTMD items), the intervention, and an immediate post-test (identical to the pre-test but with trailing demographic items), (iii) an "open" condition (similar to the sandwich condition, but "open-faced," as it used no pre-test) and (iv) a no-post-test condition to assess possible experimental demand effects on ratings/changes re GW acceptance. To avoid participant fatigue, the set of mixed statistics in each condition was split in half (creating two sets, A and B, each with equal numbers of both misleading and representative statistics) and exposed participants to half rather than all the statistics in pre- and post-tests, counterbalancing conditions. (I.e., for every sub-condition in which set A followed by B, a sub-condition had set B followed by A.) To assess whether the way the statistics were split would affect participants' ratings, we added another kind of control condition (v) in which participants would rate all 14 of the GW statistics. For a visual overview of study conditions, see Table 2. (Nb: data presented herein are from a larger study, the full results of which are too voluminous to be described in this space.)

Table 2: An overview of the basic study conditions.

(i) No-Intervention Control	Pre-test A	---	Post-test B
	Pre-test B		Post-test A
(ii) Sandwiched Intervention	Pre-test A	Curriculum	Post-test B
	Pre-test B		Post-test A
(iii) No Pre-Intervention Test	---	Curriculum	Post-test A
			Post-test B
(iv) No Post-Intervention Test	Pre-test A	Curriculum	---
	Pre-test B		
(v) Item Mixture	All 14-statistics (A and B)		
(vi) Explained Mix.	All 14-statistics (A and B) + explanations		

Note that each participant who received the blank-first statistics rated the representativeness of each statistic *twice*––once upon initially seeing the statistic with a blank instead of the crucial number and a second time after estimating that missing number and receiving feedback on that estimate.

Because Chi and others (e.g., Chi, De Leeuw, Chiu & LaVancher, 1994) indicate that self-explaining leads to deeper understanding, we also sought to assess whether explaining one's misleadingness/revealingness ratings would influence the ways in which one rated. To do so, we added yet another condition for the all-14 statistic set (vi), in which we made explanations of ratings of each statistic's revealingness/misleadingness mandatory.

All participants were debriefed at the survey's end in case the act of merely rating the statistics inadvertently caused their GW acceptance to dip. The debriefing included a full explanation of GW's mechanism *and* a graph of Earth's temperature rise since measurements began (around 1880).

Procedures, Vettings, and Participants

All conditions were run in parallel, and 613 participants were recruited through Amazon's Mechanical Turk (MTurk) and paid $1.15-$1.50 (with the range reflecting differential time-requirements of heterogeneous conditions and changes after experience with early participant-batches). Each participant was randomly assigned to his/her condition and the participant-batches occurred during 5/9/17 – 8/3/17.

Participants' data were directly excluded if participants logged in from outside the US or indicated non-US citizenship or residency. Other exclusion criteria were—as appropriate for condition—based on specific catch items (which appeared throughout the intervention and pre/post-tests), participants' durations in answering various portions of the pre/post-tests, and self-assessment of how much of the curriculum one had read. The total number of exclusion points for each condition was calculated and participants were excluded if they scored more than 25% of the point-total possible for a condition.

Out of 613 participants who completed the experiment, 41% were men (and 58% women). As 76 participants were excluded, 537 participants' data were analyzed. Participants' ages were from 18-80 years old, with the mode in the 31-35 range, with 42% identifying as Democrats (the US's largest party), with the remainder mainly as Republicans and Independents. Tea Party affiliation was 6%. Participants' mean social and economic conservatism ratings were respectively 3.93 and 4.69 (on 1-9 scales).

Results and Discussion

The first hypothesis assessed was whether exposure to a mixed set of misleading and representative statistics about global warming would change participants' overall GW acceptance or whether the misleading information would obviate the representative information. For transparency, -4 to +4 scales (for misleadingness-to-representativeness) were recoded as 1-9 scales. It should be noted more generally that participants used mostly the upper half of the scale and thus more often rated statistics as either representative—or at least pointless (the center rating)–rather than wholly misleading. A significant increase in GW acceptance (pre-to-post exposure) was obtained for the mixed set of regular GW statistics ($t(120)=-2.619$, $p<0.01$), but additional processing prior to receiving the relevant numbers as feedback caused no such effect on GW acceptance—as data from the blank-first statistics' participants show ($t(107)=0.451$, $p=0.653$; see Table 3). (Note: none of these data include conditions involving our curriculum; for curriculum-involved data, see below.) The misleading statistics were hardly inert, even though the regular-statistics mixture boosted global warming acceptance; Table 3's +.16 gain is less than observed in non-mixed conditions reported by Ranney and Clark (2016) and Ranney et al. (2019). But as in those works and in Velautham, Ranney, and Brow (2019), the gain was *not* associated with liberalism—showing no polarization.

Table 3: Changes in Global Warming acceptance means.

Condition	Pre-test acceptance	Post-test acceptance	Acceptance change
Regular	6.69	6.85	+0.16**
Blank-first	6.96	6.93	-0.03

To study differences between participant interactions with statistic-type, we contrasted (a) representativeness ratings for the regular-item statistics and (b) the *first* such ratings for the blank-first statistics' quantities (i.e., prior to the numbers being revealed as feedback), using data from the no-explanation control conditions and the pre-tests of relevant conditions.

Eight of the 14 GW statistics show statistically significant ratings differences between the blank-first and regular incarnations of each statistic. Of these differences, six are among the statistics we pre-identified as "misleading," and for each of the six, the mean regular-item rating is consistently lower (i.e., more misleading) than the average blank-first rating, indicating that people consistently found the misleading global warming statistics with the numbers more misleading, compared to the equivalent blanked statistic. Accordingly, for each representative statistic, the mean item rating for each statistic is either the same or higher (i.e., more representative) than the mean blank-first, pre-feedback, rating. These surprising results cohere with the finding that there were statistically significant ratings differences between the regular-item and blank-first conditions across both the full set of the seven representative statistics ($t(1692.7)=3.558$, p<0.01) and the seven misleading statistics ($t(1691.4)=-10.247$, $p<0.01$). Table 4 also shows that participants in the regular-statistic conditions were better at differentiating between representative and misleading statistics, due to a four-fold larger difference in mean rating between the representative and misleading statistic-sets (M(rep)=6.91 vs. M(mis)=5.22), relative to the comparable blank-first data (M(rep)=6.60 vs. M(mis)=6.20). Participants in the regular-statistic conditions also yielded a higher range of mean ratings (4.66-7.25) for the 14 items, compared to people in the blank-first conditions (5.68-6.83), with such blank-first participants more likely to identify the most misleading items as merely pointless rather than misleading.

Table 4: Representative vs. misleading statistics' representativeness means, and differences, by statistic-type.

	Regular-stats (1-9 scale)	Blank-first stats (1-9 scale)	Regular-stats vs. blank-first
Representative GW statistics	6.91	6.60	+0.31**
Misleading GW statistics	5.22	6.20	-0.98**

Recall that blank-first participants rated the revealingness of each statistic twice—before *and* after getting feedback on their estimates of the missing quantity. Differences between their first and second representativeness ratings help us understand participants' processes in evaluating the GW statistics. Ratings changed significantly after numerical feedback followed estimates for ten of the 14 statistics. Of these statistics, the representativeness rating increased (from the first to the second rating) for the *representative* statistics (i.e., they were rated as "more representative") yet the ratings *decreased* for the *misleading* statistics (i.e., they seemed "more misleading"). Table 5 shows this reflected in the mean ratings across all seven representative statistics, which significantly increased ($t(850)=11.84$, $p<0.01$) and the mean rating across all seven misleading statistics, which significantly *decreased* ($t(850)=-7.7078$, $p<0.01$) from the first rating (with a blank instead of a numeric value) to the second rating (with the correct number filled in). These results cohere with prior efforts to foster numerically-driven inferencing mechanisms (NDI; e.g., Ranney et al., 2008; Ranney et al., 2016) to help differentiate between misleading and representative statistics in the GW domain.

Table 5: Initial blank-first vs. second (i.e., post-estimation & -feedback) blank-first representativeness ratings for all representative and misleading GW statistics.

	Initial blank-first rating (M)	Second blank-first rating (M)	Blank-first ratings change due to feedback
Representative GW statistics	6.60	7.11	+0.51**
Misleading GW statistics	6.20	5.63	-0.55**

Besides rating the representativeness for a second time after estimating and receiving feedback on their estimate, participants in the blank-first conditions also rated their surprise upon that feedback. As one might expect for participants (and Americans) who, on average, accept GW's reality, Table 6 shows that they were significantly more surprised at the feedback for the misleading statistics compared to the representative statistics ($t(1686.3)=-2.898$, $p<0.01$).

Table 6: Misleading Statistics generated greater surprise.

	Mean Surprise	(Stand. Dev.)
Representative GW statistics	4.84	(2.86)
Misleading GW statistics	5.22	(2.62)

To assess the curriculum's effectiveness, we compared pre- to post-test changes in GW acceptance from the regular-statistics-*only* and blank-first-statistics-*only* conditions with data from their counterpart-conditions that *included* the curriculum described above (see Table 7).

Table 7: Statistics-type by curriculum-presence means.

Condition	Pre-GW Acceptance	Post-GW acceptance	Change in GW acceptance
Regular stats only	6.69	6.85	+0.16**
Blank-first stats only	6.96	6.93	-0.03
Regular stats & curriculum	6.84	6.88	+0.04
Blank-first stats & curric.	7.19	7.09	-0.10

The results indicate that only participants in the statistics-only conditions showed a statistically significant increase in GW acceptance ($t(120)=-2.6186$, $p<0.01$). However, this effect is fully due to the *regular-statistics*-only condition increasing GW acceptance in the absence of the curriculum. Unpaired t-tests accordingly indicate that there was no statistical difference in pre-to-posttest changes in global warming acceptance for the regular stats only (M=+0.16) and the regular stats with the curriculum (M=+0.04) conditions ($t(54.574)=0.68975$, p=0.4933), nor between the blank-first stats only (M=-0.03) and the blank-first stats with the curriculum (M=-0.10) conditions ($t(64.283)=0.56411$, p=0.5746).

Finally, we also replicated many prior results showing significant negative relationships between GW acceptance and nationalism in both the pre-test, r(318)=-0.34, p<2.2e-16 and the post-test, r(314)=-0.34, p<2.2e-16.

Summary of Results. Overall, exposure to a mixed set of misleading and revealing global warming regular statistics (i.e., statistics containing full numerical information up front) gratifyingly resulted in significantly increased global warming acceptance. Participants were also considerably better able to distinguish between the misleading and representative statistics when they were shown regular statistics compared to statistics that initially have a blank where the key number would be. However, the act of estimating a missing value and receiving feedback on that estimate caused participants to better distinguish between the misleading and representative global warming statistics––such that their second ratings were comparable in representative-misleading differential (+1.48 points) to the differential exhibited by the regular-statistics participants (+1.69, which was over a less attenuated range). Furthermore, participants in the blank-first conditions were more surprised at receiving the misleading GW statistics, compared to the representative statistics. Finally, exposure to the brief curriculum neither significantly impacted participants' GW acceptance, nor better enabled them to identify misleading statistics.

General Discussion

This experiment demonstrates that exposing people to even a balanced mixture that includes half-misleading statistical information about global warming can lead to statistically significant increases in GW acceptance. Participants assigned to rate the revealingness of the GW statistics were also much better able to differentiate between the misleading and representative statistics when there was a number in the statistic compared to when it was blanked out. Additionally, the process of estimating the missing quantity and getting feedback on the estimate helped participants to better differentiate between the revealing and misleading GW statistics. Exposure to a brief curriculum, however, did not better enable participants to distinguish between a set of representative and misleading statistics. This lack of an effect was likely due to the fact that the curriculum was a heavily (and perhaps, overly) condensed version of a week-long in-person training for journalists, which included many varied numeracy-based exercises and in-person discussions with experts (Ranney et al., 2008). Given this, we predict that expanding the curriculum, especially to include more examples of misleading statistics, would show enhanced effectiveness for this kind of training.

The negative correlations we noted between GW acceptance and nationalism has previously been explained by Ranney's Reinforced Theistic Manifest Density (RTMD) theory (e.g., Ranney, 2012; Ranney & Thanukos, 2011) and has been demonstrated and replicated in many studies. Indeed, Ranney et al. (2019) showed the relationship to even be bi-causal. The negative causality between GW acceptance and nationalism is consistent with participants feeling threatened or frightened by the idea of GW, and thus seeking the solace of stewardship associated with spirituality or organized religion (which, at least in a U.S. context, is associated with an increased identification with one's nation). Another interpretation is that people perceive GW as a phenomenon threatening themselves as individuals, and they therefore crave increased identification with the collective group of the nation in response.

Future Work

One control condition required participants to explain their statistics' representativeness ratings. Participants in other conditions also often explained their ratings, so a wealth of qualitative data to code exists, which will offer further insight into the criteria with which participants rated statistics' revealingness. These may support conclusions from the quantitative data or serve as extra analysis foci. For instance, the curriculum might be alternatively evaluated based on the number of explanations that evoked one of its four criteria for assessing how revealing/misleading a statistic is. Such analyses may serve to improve the curriculum, given that the present version seemed overly shortened from the one-week mini-course that inspired it.

In addition to collecting explanations, participants' answers to the global warming *mechanism* questions in the pre- and post-test were collected. Coding these answers (as many of our past studies have done) may help determine whether exposure to either the mixed set of representative and misleading statistics about global warming or exposure to the curriculum yielded changes in GW knowledge. Analyses could also determine whether a relationship exists between participants' GW knowledge and their ability to differentiate between the misleading and revealing GW statistics. Finally, one can analyze participants' estimates for the blank-first statistical incarnation in more depth, to see if they can provide insight into participants' cognition regarding GW. While some preliminary analysis has been carried out in this vein, due to the fact that the statistics consist of doubly-bound and more unbounded estimates, prior analyses (e.g., Rinne, Ranney, & Lurie, 2006) indicate that different formulas may need to be used concurrently to be able to get a sense of the accuracy of each estimate.

Conclusions

A functioning democracy relies on a well-informed population that has the freedom, agency, and judgment to make decisions in their best interests. If people are misinformed, they may make decisions for themselves or others that conflict with their best interests, yielding serious personal and societal consequences. The results of this experiment show that exposure to factual, veridical GW information, even interspersed with misleading GW information, can increase GW acceptance. The gain was not associated with liberalism, showing no polarization. Our results also indicate that, at least when contrast is available, people are generally better at distinguishing between revealing and misleading statistics than they are often given credit for.

Nonetheless, the effectiveness of our (micro-)*curricular* manipulation in our experiment was modest, having minimal effect on participants' ability to distinguish between the misleading and representative GW statistics. This result suggests that people in the context of this online experiment were more reliant on numerical information when determining whether a statistic related to global warming is representative/revealing, as opposed to depending more on contextual information—such as source and scope (features that our curriculum highlighted). This is supported by participants' increased ability to distinguish between the representative and misleading statistics with the regular statistics (which contained full numeric information) compared to the blank-first variants, which contained only contextual information without numbers. This reliance on numerical information is also indicated by the increased ability of participants in the blank-first conditions to distinguish between the misleading and representative GW statistics once they had been given numerical feedback on their estimates (see Tables 4 and 5).

Such numeric entities are represented in some of the seven kinds of interventions that our research group has demonstrably used to increase participants' acceptance that anthropogenic global warming is occurring: Besides (1) compelling statistics directly involving global warming (e.g., Ranney & Clark, 2016; Ranney et al., 2019) and (2) (less directly) statistics inhibiting U.S. super-nationalism (Ranney, et al., 2019), other compelling interventions that increase GW acceptance include (3) texts and (4) videos explaining the physical-chemical mechanism of global warming (Ranney & Clark, 2016; Ranney et al., 2019), as well as (5) graphs of Earth's temperature since the 1880's (Ranney et al., 2019), (6) sea level rise information (e.g., maps and economic information; Velautham, et al., 2019), and (7) a text explaining how increased CO_2 concentrations can reduce human thinking abilities (Kihiczak, Ranney, & Romps, 2020). (We are presently assessing the degree to which an eighth kind—a text about why climate scientists should largely be trusted [Senthilkumaran, Velautham, & Ranney, 2020; cf. Velautham & Ranney, 2019]—and a ninth kind [explaining the carbon cycle] are similarly compelling.) Examples of the compelling global warming statistics, and some of the other kinds of interventions, can be found at our public-outreach site: HowGlobalWarmingWorks.org (which has spawned over one million page-views; Ranney & Lamprey, 2013-2020).

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