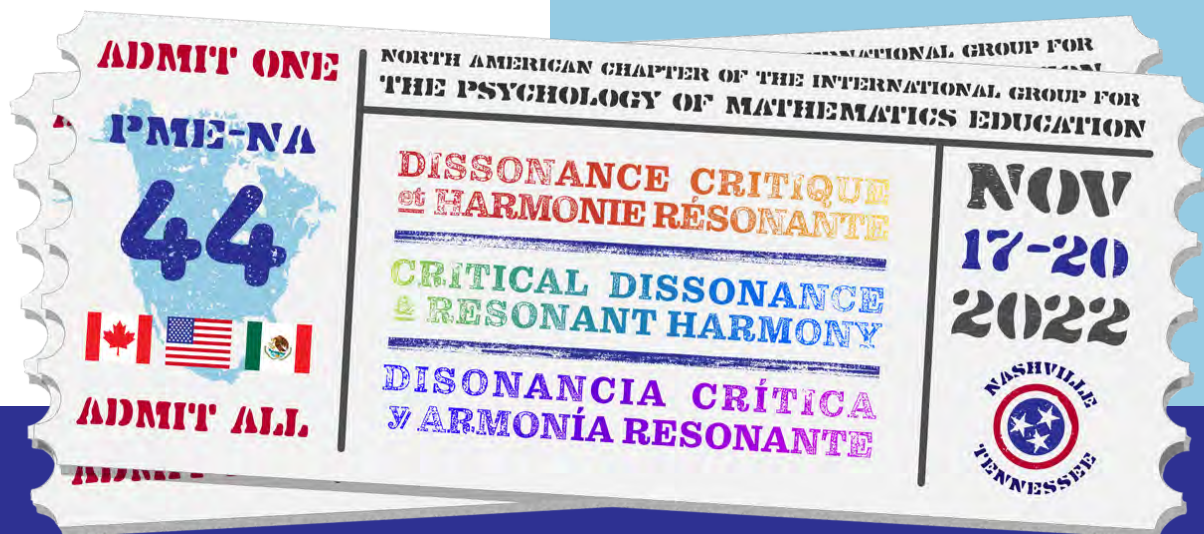


2022

# PROCEEDINGS OF THE 44TH ANNUAL MEETING OF THE NORTH AMERICAN CHAPTER OF THE INTERNATIONAL GROUP FOR THE PSYCHOLOGY OF MATHEMATICS EDUCATION

CRITICAL DISSONANCE AND RESONANT HARMONY



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# Proceedings of the Forty-Fourth Annual Meeting of the North American Chapter of the International Group for the Psychology of Mathematics Education

## Critical Dissonance and Resonant Harmony

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## Land Acknowledgement:

The PME-NA 44 Conference is held on unceded Indigenous land including the traditional homelands of the Cherokee, Shawnee, and Yuchi. The connections of Indigenous Peoples to this land continues to the present day. As we begin our conference it is important to acknowledge our place, both geographically and historically, paying tribute to the land and our ancestors—and honoring both. We note that just speaking the word Tennessee is a tribute to a first nations' word for “where the river bends.” The genocide, forced displacement, and cultural erasure of indigenous peoples resulting from the colonization of this land is particularly felt here, where the Trail of Tears cut through Middle Tennessee. In the midst of this history, Native American Indians tell their story today—including the joy of return. Founded in 1980, the Native American Indian Association of Tennessee is working to improve the quality of life for Indigenous People in this state. This includes raising funds to one day build the Circle of Life Indian Cultural Center, which will showcase a research library, exhibit halls, emergency relief support, job training, and education. These efforts help to close the circle of hatred and prejudice so that all Tennesseans can come together in freedom and pride.

An important goal of land acknowledgments is to increase support of local Indigenous communities. You can support the work of the Native American Indian Association of Tennessee by donating at [naiatn.org](http://naiatn.org). You can also learn more about the history of Tennessee's Indigenous communities by visiting the First Peoples exhibit at the Tennessee State Museum, which is about 3 miles from the conference site. More information is at [tnmuseum.org](http://tnmuseum.org).

This statement was created in conversation with local Indigenous leaders and informed by the Native Governance Center's Guide to Indigenous Land Acknowledgment.

# CLIMATE CHANGE BY THE NUMBERS: HOW NUMERICAL ESTIMATION CAN SUPPORT SCIENCE LEARNING

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*Prompting people to estimate climate change numbers before showing them the true value can shift learners' attitudes and conceptions. Yet, interventions created for such a learning experience are not easily accessible to the general public. The purpose of this preregistered study was to address this research gap by developing and testing an openly accessible online intervention that presents participants with novel numbers about climate change after they estimate those numbers. An experimental online study design was used to investigate the impact of the intervention on undergraduate students' climate change understanding and plausibility perceptions. Findings revealed that posttest climate change knowledge was higher among those randomly assigned to use the app compared with those assigned to a control condition, and that supplementing this experience with numeracy instruction was linked with more robust gains.*

Keywords: climate change education; conceptual change; numerical estimation

Misconceptions about climate change are widespread in the USA. For example, as of September 2020, only 55% of adults in the USA correctly believed that most climate scientists think that climate change is happening, suggesting that the remaining 45% hold a serious misconception (Marlon et al., 2020). Fortunately, many approaches exist that have the potential to shift these misconceptions.

Numbers found in the news or online can be a powerful tool for science learning. For example, I encourage the reader to take a moment to estimate in the following quantity: What is the percentage change in the world's ocean ice cover since 1960? The true value may surprise you (see footnote).<sup>1</sup> Presentation of novel data after people first estimate that data can elicit more explicit reflection on the novel evidence and integration of supported claims (Richter & Maier, 2017) and can subsequently shift people's attitudes, beliefs, and misconceptions to be more aligned with scientists, particularly with regards to climate change (Ranney & Clark, 2016; Ranney et al., 2019; Rinne et al., 2006; Thacker & Sinatra, 2022). These findings suggests that just a handful of numbers can incite conceptual change. Findings also show conceptual change occurring as a result of such interventions are moderated by people's willingness and openness to reason with new evidence (Thacker & Sinatra, 2022). However despite these promising findings, the interventions created for these studies are not easily accessible to the general public and the extent to which conceptual changes endure over time is not well known.

The purpose of this preregistered conceptual replication study (Plucker & Makel, 2021) was to address this research gap by developing and testing a novel and openly accessible online intervention that presents participants with novel numbers about climate change after they estimate those numbers. The study uses an experimental design to investigate the impact of the intervention on undergraduate students' science learning and test whether affective and motivational constructs that are hypothesized to moderate this change, as hypothesized in models of conceptual change.

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<sup>1</sup> The change in the world's ocean ice cover since 1960 is a 40% decrease (Ranney & Clark, 2016).

## Theoretical Framework

### Plausibility Judgments for Conceptual Change

The Plausibility Judgments for Conceptual Change model (PJCC), proposes that novel information (such as surprising data) can be a catalyst for conceptual change because it can prompt learners to appraise or reappraise the plausibility of their existing beliefs (Lombardi, et al., 2016). When people encounter novel information such as a surprising number about climate change, they first process the information for validity—perhaps by considering the credibility of the source and estimating whether the information seems reasonable—and then make a judgment of the plausibility of the conception supported by the new information. The extent to which people explicitly evaluate the plausibility of a conception depends, in part, on their motivation, emotion, and views about knowledge (or epistemic dispositions). More explicit plausibility evaluations are thought to lead to increased potential for conceptual change. For example, when a person estimates a number, they may draw from their prior knowledge or apply quantitative reasoning skills. Such an explicitly crafted estimate may better prepare the learner to interpret and assess the validity of a scientifically accepted value when later presented with it (c.f., Lombardi et al., 2016; Richter & Maier, 2017).

### Numerical Estimation

Numerical estimation is an educated guess for a quantity that can draw from a person's prior experiences and understanding of number and operations (Dowker, 2005). Understanding and estimating magnitudes of quantities is considered to be central to the development of number concept (Siegler, 2016) and represents an important skill that is emphasized in both mathematics and science K–12 standards (Cheuk, 2012).

Of the common categories of numerical estimation skills (e.g., computational estimation and numerosity; Reys & Reys, 2004), research on measurement estimation is the most relevant for this study. Measurement estimation concerns the explicit estimation of real-world measures (Sowder & Wheeler, 1989) and is useful for understanding factors that help people judge whether real-world quantities are reasonable and valid. Findings suggest that people's estimation accuracy and judgments of reasonableness improve when they use measurement estimation strategies, such as a tolerance for error and impression in estimates (Shimizu & Ishida, 1994; Thacker et al., 2021), flexible techniques for rounding digits (Joram et al., 1998), and use of the benchmark strategy—the use of known and given values to estimate unknown values through processes of analogy, association, mental iteration, and/or proportional reasoning (Brown & Siegler, 2001; Joram et al., 1998, Siegler, 2016). For example, when asked to estimate a “real world” quantity, a skilled learner might draw from their prior experiences, recall related quantities, and mathematically manipulate them to more accurately arrive at an estimate. Such an explicitly crafted estimate might better prepare the learner to interpret and assess the validity of a scientifically accepted value when later presented with it (c.f., Lombardi et al., 2016; Richter & Maier, 2017).

### Numerical Estimation for Conceptual Change

Experimental research has found that presenting people with novel climate change numbers after they estimate them can support climate change learning, and that supplementing such an experience with instruction on numerical estimation strategies and prompts to activate reflection can positively impact learning (Ranney & Clark, 2016; Thacker & Sinatra, 2022). For example, Thacker & Sinatra (2022) found that asking people to estimate climate change numbers before presenting them with the true value led to increased climate change knowledge when compared with a control group that read an expository text about the greenhouse effect. Further, although

they found no main effects of modifying the intervention with either estimation instruction or prompts to activate reflection, they did find learning gains when including *both* modifications among individuals who were willing and open to reason with new evidence. Yet, despite these promising findings, this intervention was used in a closed setting and was not openly accessible to the public. Further, the extent to which conceptual changes endured over time was not well documented. Also, no explanation or justification for the validity of the “true values” were provided, which may have dampened people’s perceptions that climate change is plausible.

### **Preregistered Research Questions and Hypotheses**

The current study aimed to test whether the findings of Thacker & Sinatra (2022) would replicate when the intervention was modified to be (a) openly accessible, (b) include estimation accuracy feedback, (c) include justification for each number estimated, and (d) when the posttest assessment was completed ten days after the intervention. Namely, I sought to answer the following preregistered research questions (for the full anonymous preregistration, see <https://bit.ly/3rP2m9c>):

- RQ1. To what extent would estimation of and exposure to novel climate change data using an online learning intervention improve learners’ climate change knowledge and plausibility judgments compared with reading an expository text?
  - (H1) I hypothesized that people assigned to the intervention conditions would have greater knowledge at posttest when compared with people assigned to read an expository text. I anticipated no significant differences in climate change plausibility perceptions between the intervention groups and the comparison group at posttest or delayed posttest.
- RQ2. To what extent do warm constructs (i.e., mathematics anxiety and epistemic dispositions) moderate the effects of the interventions on knowledge and plausibility?
  - (H2.1) Math anxiety: I anticipated that individuals with high math anxiety would benefit less from the mathematics skills instruction. That is, I expected that math anxiety would negatively moderate the effects of the intervention modified with estimation instruction when the outcome is climate change knowledge or plausibility perceptions.
  - (H2.2) Epistemic dispositions: I anticipated that individuals with higher levels of active open-minded thinking would benefit more from the intervention and modified intervention compared with the comparison condition when the outcome was climate change knowledge. That is, I expected that active open-minded thinking would positively moderate the effects of the intervention. I also anticipated that there would be a significant main effect of active open-minded thinking on plausibility perceptions, but no significant interactions with the experimental conditions.
- RQ3. To what extent does enhancing the intervention with instruction on estimation strategies change learners’ climate change knowledge and plausibility?
  - (H3) I hypothesized that supplementing the intervention with instruction on estimation skills would lead learners to report more scientific knowledge about climate change compared with those who are assigned to the intervention but without estimation instruction. I expected no significant differences in climate change plausibility between these conditions.

One additional research question was posed in the preregistration concerning whether self-reported estimation strategies differed across conditions. Related analyses are still underway.

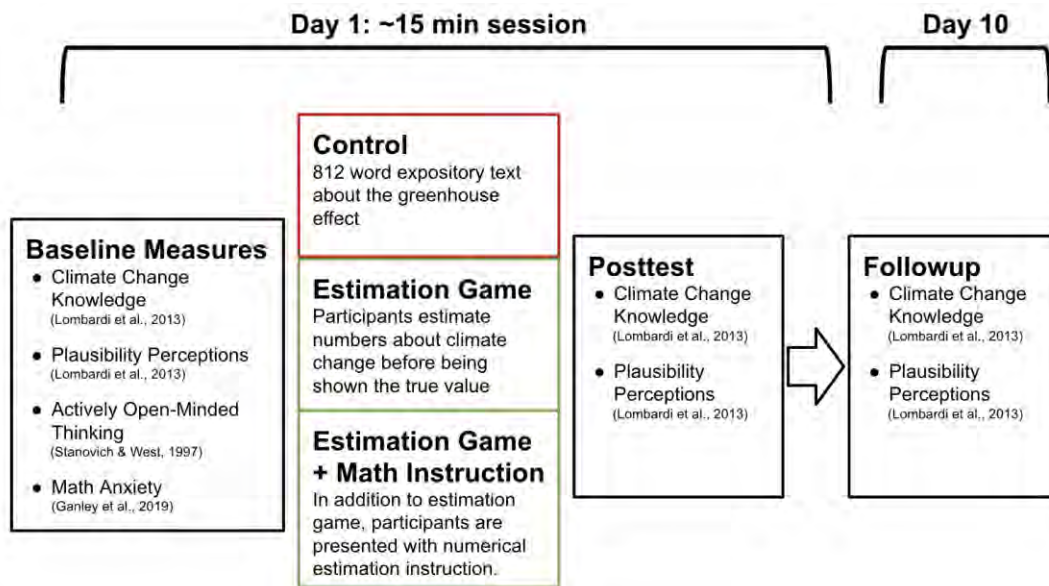


## Methods

### Participants and Procedure

I formed a national online Qualtrics panel of  $N = 605$  undergraduate students to participate in an experimental online survey. To obtain this sample, Qualtrics representatives initially used multiple platforms to widely share a survey link online, 2651 people initially clicked on the link to participate, but 2046 were dropped from the analysis because they either did not meet the eligibility criteria (over 18 and a full-time undergraduate student), did not pass an attention check, or because they were flagged as a “speeder” by the algorithm created by Qualtrics. There was no missing data at pretest or posttest. Of the 605 students who met this criteria, 57% agreed to participate in a followup study, and 88 (15% of the analytic sample) completed a short followup survey 10 days after completing the initial intervention.

Participants in the main analytic sample were 20.3 years old on average, 74% Female, 15% Male, 3% nonbinary/other, 56% White, 19% African American, 17% Asian American, 5% Two or More Races, and 2% American Indian or Alaskan Native. All participants (a) completed a pretest to measure their misconceptions about climate change, plausibility judgments about climate change, mathematics anxiety, and prior epistemic dispositions, (b) were directed to a web app that randomly assigned them to one of three conditions (control group that read an expository text about the greenhouse effect, the intervention, and the intervention supplemented with estimation instruction), (c) were directed back to the original survey where they completed an identical posttest of knowledge, plausibility perceptions, and a demographics questionnaire, and (d) were contacted ten days later to complete the knowledge and plausibility perceptions measured again (but only if they had initially indicated that they agreed to be contacted in the demographics section of the posttest). For a summary of the procedures, see Figure 1.



**Figure 1. Visual Representation of the Survey Flow, Materials, and Procedures**

### Materials

All survey materials and intervention texts are available in the supplemental materials (<https://bit.ly/3rP2m9c>), also see Appendix A for select excerpts.

## Conditions

There were three experimental conditions: the intervention group, modified intervention group, and control group. Students in the baseline intervention (also referred to as the “Estimation Game”) estimated 12 climate change related numbers before being presented with the scientifically accepted answer, a short explanation to justify the scientifically accepted answer, and accuracy feedback. Students in the modified intervention condition completed the Estimation Game, but prior to the game, they engaged with instructional text that emphasized three numerical estimation strategies—tolerance for error, the benchmark strategy, and flexible rounding—with examples and two checks for understanding. These three strategies were found in prior research to be productive for this specific task (Thacker et al., 2021). Students in the control group were presented with an 812-word expository text about the greenhouse effect adapted from Lombardi et al., (2013). See Figure 1 for a summary of the procedures and Appendix A for more detailed text excerpts and screenshots). All three experimental conditions were presented in an openly accessible, open-source online web app [<http://143.110.210.183/>; also see Thacker et al., 2021].

## Dependent variables

**Climate change knowledge.** Knowledge of climate change was measured using seven items adapted from the Human Induced Climate Change Knowledge measure (HICCK; Lombardi et al., 2013). Participants responded as to whether they believed that *climate scientists* would believe that certain statements are true (e.g., “Most of the world’s glaciers are decreasing in size. This is evidence of climate change”). Responses were on a seven-point agreement scale. Participants completed this scale pre-intervention, post-intervention, and at the 10-day followup. All were reliable at conventional levels ( $\alpha_{\text{pre}} = .65$ ,  $\alpha_{\text{post}} = .74$ ,  $\alpha_{\text{followup}} = .77$ ).

**Plausibility perceptions.** Perceptions of plausibility that humans are responsible for climate change were measured using four items adapted from the Plausibility Perceptions Measure (PPM; Lombardi et al., 2013). These items were intended to capture participant’s *personal* positions on whether humans are responsible for climate change as they responded to statements (“Evidence from around the world shows that the climate is changing in many regions”) on a six point agreement scale from 1 = *Highly Implausible (or even impossible)* to 6 = *Highly Plausible*. This scale was also completed at pretest, posttest, and during the followup and was reliable at conventional levels ( $\alpha_{\text{pre}} = .81$ ,  $\alpha_{\text{post}} = .85$ ,  $\alpha_{\text{followup}} = .83$ ).

**Estimation strategy reports.** Participants in intervention conditions also provided open-ended descriptions of strategies that they used to estimate numbers. Coding and analysis of this variable is still underway.

## Covariates

**Epistemic dispositions.** Baseline epistemic dispositions were measured using the Actively Open-Minded Thinking scale (AOT; Stanovich & West, 1997) that captures participants’ willingness to reason with novel evidence using seven items (e.g., “People should take into consideration evidence that goes against their beliefs”) using a seven point agreement scale ranging from 1 (completely disagree) to 7 (completely agree;  $\alpha = .71$ ).

**Math Anxiety.** Participants also completed a Mathematics Anxiety Questionnaire (Ganley et al., 2019) consisting of nine items (e.g., “I get a sinking feeling when I think of trying to solve math problems”) with five response options ranging from 1 (Not true of me at all) to 5 (Very true of me;  $\alpha = .93$ ).



## Analytic Strategy

To assess the effects of the interventions on the knowledge and plausibility outcome variables (RQ1 & RQ3), I used ordinary least squares regression with robust standard errors using a separate model for knowledge and plausibility perceptions. Predictors were the treatment condition and pre-test scores. To assess moderating effects (RQ2), I repeated these analyses after adding math anxiety and actively open-minded thinking as moderators of the treatment condition, with separate models for each moderator.

To test whether learning was retained ten days after the pre-test (an exploratory question), followup knowledge and plausibility scores were used as main outcomes in two separate regression models with experimental condition as a predictor and pretest scores as covariates.

## Results

All coefficients, standard errors, and *p*-values from regression models are presented in Table 1.

**RQ1: Main Effects of the Intervention.** With regards to knowledge as the main outcome, participants in both intervention conditions outperformed the control group. This difference was significant for the modified intervention before and after adjusting for moderating variables and interactions, whereas for the unmodified intervention, the effect was only significant before adjusting for moderators. When plausibility perceptions were the main outcome, no significant main effects of the intervention were found. As such, H1 was confirmed.

I also used contrasts to test whether findings replicated those of Thacker & Sinatra (2022), revealing that posttest climate change knowledge was indeed higher among those in either intervention condition compared with those assigned to a control condition ( $d = 0.30, p < .001$ ).

**Table 1. Effects of Experimental Conditions on Posttest Knowledge and Plausibility and The Moderating Effects of Math Anxiety and Actively Open-Minded Thinking (N = 605).**

	Posttest Knowledge			Posttest Plausibility Perceptions		
	No Moderator	Math Anxiety as Moderator	AOT as Moderator	No Moderator	Math Anxiety as Moderator	AOT as Moderator
	<i>b</i> (SE) <i>p</i>	<i>b</i> (SE) <i>p</i>	<i>b</i> (SE) <i>p</i>	<i>b</i> (SE) <i>p</i>	<i>b</i> (SE) <i>p</i>	<i>b</i> (SE) <i>p</i>
Estimation Game	<b>0.232***</b> (0.046) <i>p</i> < .001	<b>0.270~</b> (0.139) <i>p</i> = .054	0.016 (0.244) <i>p</i> = .946	0.232 (0.141) <i>p</i> = .102	0.190 (0.430) <i>p</i> = 0.659	-0.521 (0.791) <i>p</i> = .511
Estimation Game + Estimation Instruction	<b>0.168***</b> (0.046) <i>p</i> < .001	<b>0.387**</b> (0.137) <i>p</i> = .005	<b>0.527*</b> (0.234) <i>p</i> = .025	0.161 (0.142) <i>p</i> = .260	0.249 (0.423) <i>p</i> = .556	-0.027 (0.760) <i>p</i> = .972
Moderator		-0.014 (0.032) <i>p</i> = .670	<b>0.146***</b> (0.034) <i>p</i> < .001		0.015 (0.098) <i>p</i> = .877	<b>0.268*</b> (0.111) <i>p</i> = .016
Intervention * Moderator		-0.013 (0.045) <i>p</i> = .774	-0.040 (0.049) <i>p</i> = .408		0.014 (0.139) <i>p</i> = .919	0.146 (0.157) <i>p</i> = .353
Modified Intervention * Moderator		<b>-0.077~</b> (0.045) <i>p</i> = .084	<b>0.142**</b> (0.047) <i>p</i> = .003		-0.031 (0.138) <i>p</i> = .824	0.037 (0.152) <i>p</i> = .807
R2	0.464	0.472	0.537	0.626	0.626	0.638

*Note:* AOT = Actively Open-Minded Thinking. The comparison condition is the control condition in which participants read an expository text about the greenhouse effect. All models include pretest scores as a covariate, namely, posttest knowledge is adjusted for pretest knowledge and posttest plausibility is adjusted for pretest plausibility perceptions. Boldfaced values indicate significant results for predictors.  
~*p*<0.1; \**p*<0.05; \*\**p*<0.01; \*\*\**p*<0.001

### **RQ2: Moderating Effects of Math Anxiety and Actively Open-Minded Thinking.**

Findings revealed significant main effects of Actively Open-Minded Thinking when knowledge and plausibility were the main outcome variable, and that it moderated the effect of estimation instruction on knowledge. Thus, I found support for H2.1 and partial support for H2.2.

**RQ3: Comparison Between Intervention and Modified Intervention.** Comparing only the two intervention groups revealed no significant differences after controlling for pretest scores. This was true for both outcomes: posttest knowledge ( $p = .180$ ) and plausibility ( $p = .623$ ).

**Followup Analysis.** As noted, I followed up with willing participants approximately ten days after the intervention. Because only 15% of the analytic sample ( $n = 88$ ) completed the followup survey, pre-planned (but exploratory) multilevel analyses were underpowered. I therefore ran two separate regression models with followup knowledge and plausibility scores as the main outcomes, experimental condition as the main predictor, and pretest scores as covariates. Neither model revealed significant effects of either intervention or modified intervention groups when compared with the control (all conditional  $p > .248$ ).

### **Significance**

I sought to investigate whether the learning that occurs when people encounter novel statistics was enhanced with additional instruction on estimation strategies. Consistent with prior research, I found that students who learned from novel statistics performed about a third of a standard deviation better than a control group on a posttest of climate change knowledge (c.f., Ranney & Clark, 2016; Thacker & Sinatra, 2022).

Findings also revealed that students' willingness to reason with new evidence was a predictor of learning and moderated the effects of numerical estimation instruction. These effects of Actively Open-Minded Thinking provide support for the Plausibility Judgments for Conceptual Change Model (Lombardi et al., 2016); instruction that emphasizes the explicit evaluation of evidence appears to be most effective among those willing to consider belief-discrepant information (also see Richter & Maier, 2017). Educators might thus consider pairing estimation instruction with special emphasis on the importance of keeping an open mind when examining new types of numerical evidence, even if the evidence is contrary to students' current beliefs.

I also found no significant main effects of supplementing the Estimation Game with instruction that emphasized three key estimation strategies (tolerance for error, flexible rounding, and the benchmark strategy). This may suggest that the baseline intervention may be equally effective at encouraging explicit evaluation of quantities for most learners. It could also be that the outcome measures were not sensitive to capture the learning that occurred from this short micro-intervention. While I did find that the effects of the modified intervention was more robust to inclusion of covariates, future research should explore measuring alternate learning outcomes that are more sensitive to whether and which estimation skills were applied to support meaning-making from climate change quantities.

Another contribution of this study is that it provides mathematics instructors with a tool that enables applications of mathematical skills to learn about relevant science topics. The central intervention provides educators concerned with public understanding of science with an easily accessible learning application that can be shared and adapted to provide opportunities for students to apply numeracy skills towards making of key numbers that shape our changing environment.

## Appendix A. Examples of The Experimental Conditions

### Intervention Group (Screenshots from the “Estimation Game”)

**Do you think like a climate scientist?**

How many billions of tons of CO<sub>2</sub> are emitted by the USA each year?

(Hint: European Union, currently consisting of twenty eight countries, collectively emit 3.25 billion tons of CO<sub>2</sub> per year.)

Estimate

Billion tons of CO<sub>2</sub>

Progress...

**Do you think like a climate scientist?**

How many billions of tons of CO<sub>2</sub> are emitted by the USA each year?

Estimate  Billion tons of CO<sub>2</sub>      Actual  Billion tons of CO<sub>2</sub>

Human activity has caused more than 250 times the amount of CO<sub>2</sub> to be cast into the atmosphere compared to the levels of CO<sub>2</sub> released from natural sources after the last Ice Age. The USA is the world's second largest emitter of carbon dioxide, after China who produced 10.6 billion metric tons of CO<sub>2</sub> in 2018. Concerned citizens can make a difference by voting to reduce accelerating carbon emissions.

► Sources

Accuracy

★★★★☆

### Modified Intervention Group (Excerpts from estimation instruction that preceded Estimation Game)

Sometimes people estimate everyday numbers in their head. For example, you might quickly estimate the cost of tax and tip in your head before ordering a meal at a restaurant. These calculations are naturally very rough and imprecise, and it is okay if your guess is not perfect...

#### REFERENCE NUMBERS

Numbers that you already know (reference numbers) can help you estimate numbers that you do not know. For example, if you know that about 300 pennies fit in a small, 8oz milk carton, you can use this information to estimate the number of pennies that fit in a gallon...

#### SIMPLIFYING NUMBERS

When using reference numbers, you may want to round values to make mental computation easier. For example, let's estimate the population of California given that the population of Kentucky is 4.47 million. Before making our estimate, we first round the Kentucky population to 4 million to make the math easier, and scale this value according to our beliefs about the size of California compared to Kentucky. If you were to guess that California...

### Control Group (Excerpt of Expository Text adapted from Lombardi et al., 2013)

#### THE ENHANCED GREENHOUSE EFFECT

Many people have heard of the “greenhouse effect”, but not everyone knows what the “greenhouse effect” is exactly. The greenhouse effect refers to the way that certain gasses in earth's atmosphere keep the planet warmer than it would otherwise be. The earth's greenhouse effect is a natural occurrence...

*Note.* All materials appeared within the Estimation Game environment (<http://143.110.210.183/>). For complete intervention materials, see the supplemental materials (<https://bit.ly/3rP2m9c>).

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