NUMERICAL ESTIMATION SKILLS, EPISTEMIC COGNITION, AND CLIMATE CHANGE: MATHEMATICAL SKILLS AND DISPOSITIONS THAT CAN SUPPORT SCIENCE LEARNING

Ian Thacker
University of Texas at San Antonio
ianedgarthacker@gmail.com

Texts presenting novel statistics can shift learners' attitudes and conceptions about controversial science topics. However, not a lot is known about the mechanisms underlying this conceptual change. The purpose of this study was to investigate two potential mechanisms that underlie learning from novel statistics: numerical estimation skills and epistemic cognition. This research investigated two treatments—a numerical estimation and epistemic cognition intervention—that were expected to enhance people's ability to make sense of key numbers about climate change. Results indicated that undergraduate students (N = 516) who were given instruction on numerical estimation strategies before shown novel climate change statistics had fewer misconceptions when compared with people who did not. Findings provide emerging evidence that supporting mathematical reasoning skills can enhance conceptual change in science.

Now more than ever, people need to be skeptical of the information that they encounter online. Inaccurate, self-authored misinformation is being created and circulated at an alarming rate (see, e.g., Allcott, Gentzkow, & Yu, 2019; Kata, 2012). Internet searches for controversial science topics like climate change, genetically modified foods, and vaccinations reveal millions of articles, much of which include scientifically incorrect information (e.g., Kortum, Edwards, & Richard-Kortum, 2008; Scheufele, & Krause, 2019); and much of this misleading information relies on misleading data.

Numerical data (e.g., statistics) found in the news can be a powerful tool for conceptual change, whether that change is for better or for worse. On the one hand, prompting people to estimate just a handful of statistics about climate change and then presenting them with the actual value can shift their attitudes, beliefs, and misconceptions to be more aligned with scientists (Ranney & Clark, 2016). On the other hand, presenting people with misleading statistics can shift their scientifically correct conceptions and attitudes to be less aligned with those of scientists (Ranney & Clark, 2016). Taken as a whole, this research suggests that statistics can be used as a catalyst for conceptual change. However, the mechanisms that underlie this change process remain understudied.

The purpose of this study was to examine mechanisms that underlie the learning that occurs when people encounter novel statistical information. Namely, I draw from theory on conceptual change (Dole & Sinatra, 1998, Lombardi, Nussbaum, & Sinatra, 2016), and epistemic cognition (the active reflection on whether information is true or justified; Chinn, Rinehart, & Buckland, 2014) to examine the impact of two mechanisms of conceptual change when learning from real-world numbers—numerical estimation skills and epistemic cognition.

Theoretical Framework

Conceptual Change

When individuals encounter statistics in the news or online that conflict with their prior conceptions, conceptual change may occur. Conceptual change represents a particular kind of

learning that occurs when new information conflicts with a learners' background knowledge, leading to a restructuring of conceptual knowledge (Dole & Sinatra 1998; Murphy & Mason, 2006). Conceptual change researchers tend to describe concepts as either consistent or inconsistent with the understanding of experts and many define conceptual change as a correction of scientifically inaccurate conceptions, or *misconceptions*. For example, if a person holds the misconception that scientists believe that humans are not responsible for climate change and reads a statement that "97% of scientists agree that climate change is caused by humans," then there may be potential for the learner to question their idea and shift them to be more consistent with scientists. In this way, a single number has the potential to instigate conceptual change. Of course, there are many contributing factors and processes left unexplained in in this simplistic example, as conceptual change can be viewed as a process that is contingent upon people's motivation, emotion, and attitudes—factors that are often called *warm constructs* (see Dole & Sinatra, 1998; Pintrich, Marx, & Boyle, 1993; Sinatra, 2005; Sinatra & Seyranian, 2016). As such, the extent to which people engage with and learn from numerical data may be influenced by motivational factors such as their beliefs about their ability to succeed in mathematics (*self-efficacy*; e.g., Bandura, 1997), or emotional factors such as their trait-level anxiety associated with engaging in mathematics (*mathematics anxiety*; e.g., Ramirez, Shaw, & Maloney, 2018).

Plausibility judgments for conceptual change. When individuals encounter a novel statistic, they may implicitly or explicitly judge whether that information is plausible and then shift their conceptions accordingly. Research on plausibility judgments for conceptual change offers a useful frame for investigating these shifts in understanding. The Plausibility Judgments for Conceptual Change model (PJCC), posits that novel information (like novel statistics) can incite conceptual change because they prompt learners to appraise or reappraise the plausibility of their existing beliefs (Lombardi et al., 2016). When people encounter a novel explanation like a statistical figure, they first pre-process the information (e.g., by employing numerical estimation skills to judge the reasonableness of the number), and then make a judgment of the plausibility of the conception supported by the new information. Plausibility judgments can be either implicit or explicit. The extent to which people explicitly evaluate the plausibility of a conception depends, in part, on their views about knowledge (epistemic motives and dispositions); more explicit plausibility evaluations are thought to lead to greater potential for conceptual change—but only if the learner finds the new conception to be more plausible than their previous conception. That is, learners process statistical information and then appraise the plausibility of their initial conceptions based on this information; learners that find a novel conception more plausible than prior conceptions have higher potential for conceptual change.

Numerical Estimation

One way that learners process numbers is by estimating whether they are reasonable (e.g., Reys & Reys, 2004). Research on measurement estimation concerns the explicit estimation of real-world measures (Bright, 1976; Sowder & Wheeler, 1989) and is useful for understanding factors that help people judge whether real-world quantities are reasonable. Findings suggest that peoples' estimation accuracy and judgments of reasonableness improve when they use measurement estimation strategies, such as the benchmark strategy—the use of given standards and facts that can be applied by the learner through mental iteration and proportional reasoning to better estimate and judge the plausibility of real-world quantities (e.g., Brown & Siegler, 2001; Joram et al., 1998). For example, a person's estimate of the number of jellybeans in a container is likely to be more accurate and they will be a better judge of reasonableness of other

peoples' guesses if they are first told the number of jellybeans in a different container. Measurement estimation strategies may therefore support people's comprehension and evaluation of given real-world quantities.

Epistemic Cognition

Epistemic cognition is the thinking that people do about knowledge and knowing (Chinn, et al., 2014; Sandoval, Greene, Braten, 2016) and is hypothesized to predict the extent to which learners evaluate the plausibility of a claim in light of new information (Lombardi et al., 2016). There are multiple models of epistemic cognition (for a review, see Sandoval et al., 2016), but for the purpose of this study, I draw from the AIR model of epistemic cognition (Chinn et al., 2014). According to this model, epistemic cognition is considered to be a situated process that relies on individuals' Aims (goals and associated values of goals), Ideals (espoused standards for achieving epistemic aims), and Reliable processes for knowing (schema for producing true, justified beliefs; Chinn et al., 2014).

An Existing Learning Intervention: EPIC

Prior classroom and laboratory studies have demonstrated the impact of presenting people with surprising numbers about controversial topics on their understanding of social issues (for reviews, see Ranney et al., 2019; Yarnall & Ranney, 2017). Many of these studies are grounded in a paradigm called "Numerically Driven Inferencing" (NDI, Ranney, Cheng, Garcia de Osuna & Nelson, 2001; Ranney & Thagard, 1988), which assumes that individuals' understanding of numerical information is connected to their knowledge, attitudes, and beliefs about larger issues. One of the central techniques from this perspective is called EPIC, an acronym for an intervention which introduces novel numerical information by prompting learners to Estimate quantities, state a Preference for what they would like the quantity to be, Incorporate the answer, and then Change their preferences afterward (e.g., Ranney & Clark, 2016; Rinne et al., 2006). Studies that use EPIC often operationalize conceptual change in terms of shifts in the preferences that individuals state for given numbers (i.e., differences between the "P" and the "C" in EPIC).

In sum, I contend that in order for learners to select high quality content from which to learn, they must develop skills to evaluate epistemic aspects of new information and also develop estimation skills necessary to accurately evaluate the statistics that they encounter along the way. That is, they must learn epistemic cognition and numerical estimation skills. Currently, there is little to no empirical research that investigates the role of estimation skills and epistemic cognition in conceptual change processes. My research is therefore guided by five questions:

1. To what extent does estimation of and exposure to novel statistics regarding climate change (i.e., an adapted EPIC intervention) shift learners' knowledge of climate change?
2. To what extent does enhancing this intervention with instruction on estimation strategies change learners' knowledge of climate change?
3. To what extent does enhancing this intervention with prompts to activate epistemic aims change learners' knowledge of climate change?
4. Is there an interaction between estimation skills and epistemic thinking on conceptual change?
5. To what extent do warm constructs (i.e., mathematics anxiety, mathematics self-efficacy, epistemic dispositions, and reported surprise from reading statistical information) mediate relations between pre- and post-intervention knowledge?

Methods

To answer my research questions, I formed a nationally representative Qualtrics panel of 516 undergraduate students to participate in an experimental online survey. Participants' median reported age was 20years, and 81% identified as Female, 64% White, 11% African American, 9% Asian, 9% Hispanic, and 43% as either Liberal or Very Liberal. All participants (a) completed a pretest to measure their misconceptions about climate change, mathematics self-efficacy and anxiety, and prior epistemic dispositions, (b) were randomly assigned to one of five conditions created by a control group and combinations of two interventions (see below), and (c) completed an identical post-test of knowledge and a demographics questionnaire.

Outcome Measure

Knowledge. Knowledge of human-induced climate change was a primary outcome in this study and was measured using seven items from the 28-item human induced climate change knowledge questionnaire (HICCK; Lombardi, Sinatra, & Nussbaum, 2013). Construct and content validity of the abbreviated scale was established through pilot studies and cognitive interviews (see Thacker, 2020). The knowledge questionnaire was given to participants just prior to and immediately after instruction and was intended to measure participants' conceptions about the consensus on human-induced climate change and were selected to align with information presented in the EPIC intervention. For example, participants rated their agreement with statements such as, "greenhouse gas levels are increasing in the atmosphere" on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). The measure at pre and posttest was reliable at conventional levels (Cronbach's alpha = .85 pre, .88 post).

Covariates

Mathematics Self-Efficacy and Anxiety Questionnaire (MSEAQ). Participants' mathematics-specific self-efficacy and anxiety were measured using the Mathematics Self-Efficacy and Anxiety Questionnaire (MSEAQ; May, 2009). The MSEAQ consists of 28 items that can be divided into two subscales, mathematics self-efficacy (13 items) and mathematics anxiety (15 items). Construct validity was established in a prior study using factor analytic methods with an online sample and by establishing strong correlations with a classic measures of mathematics anxiety (s-MARS) and mathematics self-efficacy (see May, 2009). The instrument was shown to be reliable overall (Cronbach's Alpha = .96), as were the two subscales for mathematics self-efficacy (Cronbach's Alpha = .94) and mathematics anxiety (Cronbach's Alpha =.93). Average scores for the two subscales were computed and used in mediation analyses.

Epistemic dispositions. Baseline epistemic dispositions were measured using the Actively Open-Minded Thinking scale (AOT; Stanovich & West, 1997). The AOT is a measure of epistemic dispositions toward knowledge that consists of seven items. Participants reported their agreement with five statements (e.g., "Changing your mind is a sign of weakness") on a scale from 1 (*completely disagree*) to 7 (*completely agree*). The Chronbach's alpha was found to be .70 with the main analytic sample. The AOT was included in mediation analyses to observe whether epistemic dispositions mediate conceptual change outcomes, as inferred from the Plausibility Judgments for Conceptual Change model (Lombardi et al., 2016).

Surprise. Participants in the main analytic sample who were assigned to estimate quantities about climate change by way of the EPIC intervention were also prompted to report their sense of surprise after being shown the true values. Namely, participants were asked to "Rate how surprised you are by this number" on a scale from 1 (*not at all*) to 7 (*extremely surprised*). Surprise ratings had Cronbach's alpha = .82. Similar to prior research (e.g., Munnich et al.,

2007), I expected that participants' sense of surprise from exposure to novel statistics would correspond with change in climate change beliefs. Participants in the control group did not estimate climate change numbers and therefore were not prompted to report surprise.

Interventions and Experimental Conditions

Participants were randomly assigned to one of five conditions: (1) a control group in which participants were presented with an 817 word expository text about the greenhouse effect (2) the EPIC task; (3) the EPIC task accompanied with an estimation skills modification that presents learners with strategies for using the given "hints," (4) an EPIC task accompanied with an epistemic cognition modification, or (5) an EPIC task accompanied by both estimation and epistemic cognition modifications. These interventions and modifications are described below.

The EPIC task required learners to estimate 12 climate change-related quantities before being presented with the scientifically accepted answer. Six of these items were taken from Ranney & Clark (2016) and asked participants to estimate unitless proportions. The remaining six were created by Thacker (2020) to be more mathematically challenging, requiring participants to estimate raw units of length, area, volume, mass, and temperature and included a "hint" that might be rescaled to better estimate the unknown quantity (see Table 1 for sample items).

The estimation skills modification consisted of a 132-word text that provided direct instruction on how to use the "hints" embedded in half of the EPIC items to more accurately estimate unknown numbers followed by two interactive examples (see Table 1 for an excerpt). The epistemic cognition modification was intended to activate epistemic aims and consisted of an open answer text-box that appeared after each of the twelve number estimates, prompting participants to "...reflect on the differences between your estimate and the true value. How does the true value change what you know about climate change or the way you think about climate change? Explain." This prompt was intended to activate epistemic aims.

Table 1. Sample Items from the EPIC Intervention and Modifications to the Intervention.

Sample EPIC Items			
Source	# of items	Sample item	Correct Answer
Ranney & Clark (2016)	6	What is the change in percentage of the world's ocean ice cover since the 1960s? (units in %)	40% Decrease
Thacker (2020)	6	What was the average Arctic Sea ice thickness in 2008? *Hint: Arctic ice thickness was 3.64 meters in 1980*	1.89 meters
Excerpt from Numerical Estimation Strategies Modification			
Numbers that you already know 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 larger container… When using benchmarks, you may want to round values to make mental computation easier. For example...			
Excerpt from Epistemic Cognition Instruction Modification			
...Please reflect on the differences between your estimate and the true value. How does the true value change what you know about climate change or the way you think about climate change? Explain.			

Results

Preliminary analyses revealed no significant differences in pre-intervention knowledge between conditions ($F = 1.54$, $p = .187$). Skew ranged from -.78 to -.34 and kurtosis ranged from .01 to .36 for the revised knowledge measure though both failed the Shapiro-Wilk normality test ($p < .001$ for both pre- and post-knowledge), as such, both classic and robust analyses are presented. An initial omnibus test revealed significant differences between the five conditions when the seven-item knowledge score at post-test was used as the main outcome ($F = 3.126$, $p = .0147$). This finding was corroborated with nonparametric ANOVA analyses using a Kruskal-Wallis rank sum test (Kruskal-Wallis Chi-squared = 17.18, $df = 4$, $p = .001$). Raw means and standard deviations by condition and overall for all variables are shown in Table 2.

Table 2. Descriptives by Condition for the Main Analytic Sample of N = 516 Undergraduate Students.

	Min, Max	Alpha	Full Sample (n=516)		Control (n=103)		EPIC (n=103)		EPIC+EC (n=103)		EPIC+EST (n=104)		EPIC+EC+EST (n=103)	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Knowledge (Pre)	1, 5	.85	3.88	0.60	3.82	0.58	3.98	0.56	3.84	0.66	3.93	0.53	3.81	0.66
Knowledge (Post)	1, 5	.88	4.08	0.75	3.88	0.66	4.20	0.72	4.06	0.78	4.19	0.68	4.06	0.80
Knowledge Gain (Post − Pre)	-4, 4	na	0.20	0.57	0.06	0.42	0.22	0.50	0.22	0.73	0.26	0.49	0.25	0.65
Active Open Mindedness	5, 5	.70	4.84	0.86	4.74	0.81	5.03	0.89	4.83	0.83	4.83	0.89	4.78	0.85
Mathematics Self-Efficacy	1, 5	.94	3.27	0.87	3.31	0.97	3.20	0.81	3.33	0.83	3.24	0.86	3.29	0.87
Mathematics Anxiety	1, 5	.93	2.98	0.86	2.98	0.90	2.95	0.84	2.98	0.90	2.95	0.81	3.03	0.87
Surprise (in Reaction to EPIC Items)	1, 5	.82	2.83	0.73	NA	NA	2.79	0.67	2.83	0.75	2.85	0.81	2.87	0.71

Control versus all other conditions (RQ1). To address my first research question, I used contrasts to assess the knowledge of the control group compared with the combined average of the remaining four groups. A Welch's two sample t-test revealed significant differences in mean post-intervention knowledge between control ($M = 3.88$) and EPIC conditions ($M = 4.12$, $t = 3.23$, $p = .001$, Cohen's $d = .33$), as did Yuen's method of trimmed means, bootstrapped T, and bootstrapped medians (all $p < .009$). In other words, students assigned to the EPIC conditions performed about one third of a standard deviation better on the seven-item knowledge posttest when compared with the control.

Estimation intervention versus no estimation intervention (RQ2). To address my second research question, I first dropped the control from analysis to consider only the four EPIC conditions, and then used planned contrasts to compare those who were given estimation instruction with those who were not. A Welch's two sample t-test revealed a marginally significant and positive impact of the estimation intervention on post-intervention knowledge ($b = .09$, $SE = .05$, $p = .086$). After adjusting for prior knowledge, nonparametric ANCOVA methods using a Thiel-Sen estimator revealed significant differences in post-intervention knowledge scores for those at the upper third (*Difference* = .31, *95% CI* = 0.04-0.58) and fourth (*Difference* = .17, *95% CI* = 0.08-0.27) of five evenly spaced points along the range of prior knowledge, a range that includes 67% of the analytic sample. In other words, the estimation
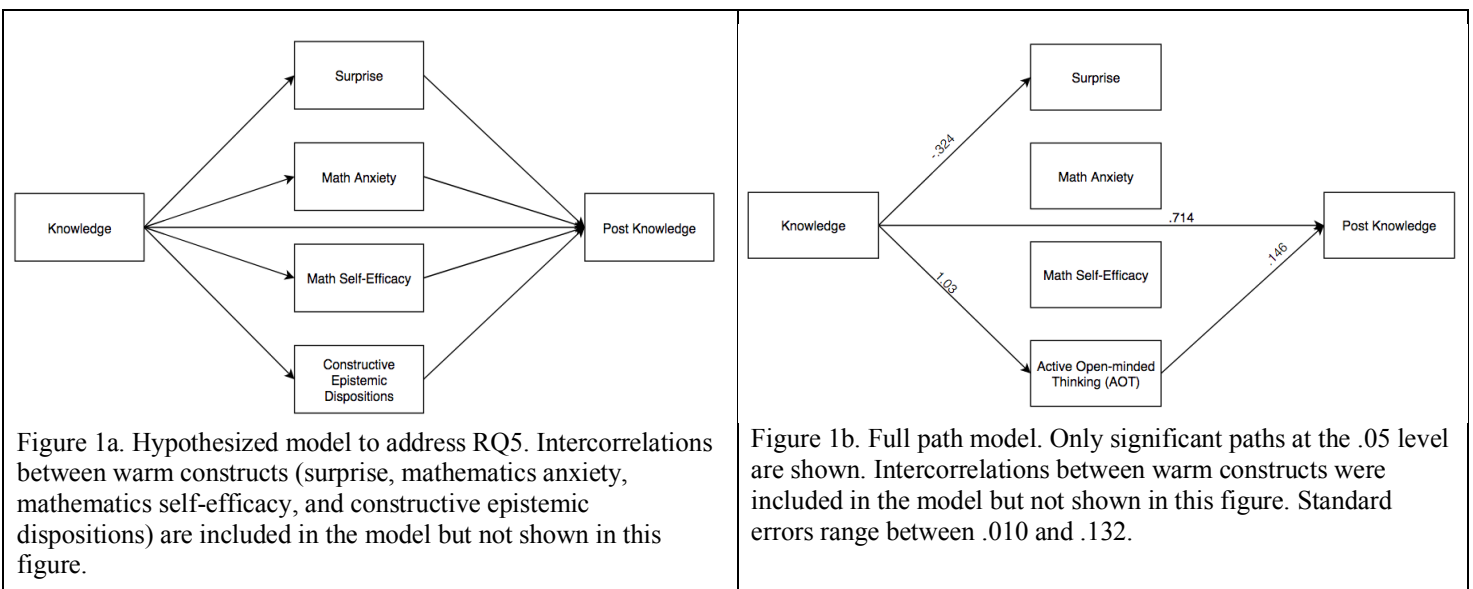
intervention appeared to be effective in shifting knowledge for participants on the upper end of the prior knowledge range.[i]

Epistemic cognition intervention versus no epistemic cognition intervention (RQ3). To answer my third research question, I again used contrasts to compare those who were given epistemic cognition prompts with those who were not after dropping the control from analysis. Contrasts revealed no significant differences on the revised knowledge scale at post-test, even after adjusting for prior knowledge.

Tests for interactions (RQ4). To answer my fourth research question, I tested for main effects and interactions of the two modifications to the EPIC intervention. I first ran classic two-way ANOVAs followed by robust two-way ANOVAs using Johansen's heteroscedastic method for trimmed means (see Wilcox, 2017, Chapter 10). Both sets of tests revealed no significant main effects or interactions when post-intervention knowledge was the outcome.

Mediating role of warm constructs (RQ5). To explore relations between prior knowledge, warm constructs, and post-intervention knowledge, I tested a hypothesized model inferred from Lombardi and his colleagues (2016; presented in Figure 1a.) using maximum likelihood estimation with robust (Huber-White) standard errors and a scaled Yuan-Bentler test statistic in R using Lavaan 0.6-3 (Rosseel, 2012). The model resulted in acceptable fit at conventional levels ($CFI = .99$, $TLI = .93$, $RMSEA = .077$; Hu & Bentler, 1999).

As expected, results revealed that warm constructs mediated relationships between prior- and post-intervention learning outcomes (see Figure 1b for all coefficients). Notably, I found indirect effects of prior knowledge on post-test knowledge through active open-minded thinking (*indirect effect = .059, p < .01*).

Figure 1a. Hypothesized model to address RQ5. Intercorrelations between warm constructs (surprise, mathematics anxiety, mathematics self-efficacy, and constructive epistemic dispositions) are included in the model but not shown in this figure.

Figure 1b. Full path model. Only significant paths at the .05 level are shown. Intercorrelations between warm constructs were included in the model but not shown in this figure. Standard errors range between .010 and .132.

Significance

I sought to investigate whether the learning that occurs when people encounter novel statistics was enhanced with additional instruction on estimation strategies or prompts to activate epistemic aims. I found that students who learned from novel statistics performed about a third of a standard deviation better than a control group on a post-test of climate change knowledge, which is consistent with prior findings demonstrating the effectiveness of EPIC for climate change learning (e.g., Ranney & Clark, 2016; Ranney et al., 2019).

I also found that enhancing this intervention with numerical estimation instruction had a small but positive impact on students' science learning; an effect that was concentrated among students in the upper range of the prior knowledge distribution. These findings provide emerging evidence that numerical estimation skills can be leveraged for improved scientific learning. Future research support students' numerical estimation skills as applied to additional policy-relevant topics.

Findings also revealed that prompts to activate epistemic aims had no detectable effect on undergraduate students learning. To date, efforts to design micro-interventions intended to shift epistemic dispositions are only emerging. Only longer interventions spanning the duration of several weeks have yielded impacts on patterns of epistemic thinking (e.g., Lombardi et al., 2013; Chinn & Buckland, 2012). More research is needed to explore whether such an intervention is possible. Related to this, I found no significant interactions between intervention conditions, likely due to the very small and insignificant effects of the epistemic cognition intervention. With improved intervention design, future research might explore whether such an interaction might exist.

Though the brief online intervention created for this study was not found to *shift* learners' epistemic dispositions, learners' *baseline* epistemic dispositions were shown to be important mediators of conceptual change processes. Namely, a path model revealed that epistemic, motivational, and affective constructs were important predictors of conceptual change outcomes, as predicted by the Plausibility Judgments for Conceptual Change model (Lombardi et al., 2016), and that epistemic dispositions significantly mediated relationships between pre-intervention knowledge and post-intervention knowledge.

Conclusions

Findings from this study contribute to better understanding the extent to which individuals shift their conceptions about climate change based on just a handful of novel statistics and illuminate mechanisms that underlie such conceptual changes. Evidence that epistemic cognition, estimation skills, motivational, and emotional factors play a role in conceptual change provide empirical support for the Plausibility Judgments for Conceptual Change model (Lombardi et al., 2016). Findings also provide emerging evidence that mathematical knowledge can be leveraged for conceptual change regarding scientific topics. By creating and testing instructional interventions, this study also provides both mathematics and science instructors and those concerned with public understanding of science with a collection of strategies for better preparing people with skills to navigate the minefield of deceptive statistics found in today's online news landscape.

---

[i] Pairwise comparisons using the Benjimani-Hochberg method revealed significant differences between post-intervention knowledge scores when comparing the control and unmodified EPIC intervention ($p = .022$, Cohen's $d = .46$) and when comparing the control and EPIC supplemented with estimation strategy instruction ($p = .026$, Cohen's $d = .46$).

References

Allcott, H., Gentzkow, M., & Yu, C. (2019). Trends in the diffusion of misinformation on social media (No. w25500). National Bureau of Economic Research.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W.H. Freeman.

Bright, G. W. (1976). Estimation as part of learning to measure. In D. Nelson & R. E. Reys (Eds.), *Measurement in School Mathematics: 1976 Yearbook* (pp. 87–104).

Brown, N. R., & Siegler, R. (2001). Seeds aren't anchors. *Memory & Cognition*, *29*(3), 405–412.

Chinn, C. A., & Buckland, L. A. (2012). Model-based instruction: fostering change in evolutionary conceptions and in epistemic practices. In K. S. Rosengren, E. M. Evans, S. Brem, & G. M. Sinatra (Eds.), *Evolution challenges: Integrating research and practice in teaching and learning about evolution* (pp. 211-232). New York: Oxford University Press.

Chinn, C. A., Rinehart, P., & Buckland, L. A. (2014). Model-based instruction: Fostering change in evolutionary conceptions and in epistemic practices. In K. S. Rosengren (Ed.), *Evolution challenges: Integrating research and practice in teaching and learning about evolution* (pp. 211–232). Oxford University Press.

Dole, J. a., & Sinatra, G. M. (1998). Reconceptualizing change in the cognitive construction of knowledge. *Educational Psychologist, 33*(2), 109–128.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55.

Joram, E., Subrahmanyam, K., & Gelman, R. (1998). Measurement estimation: Learning to map the route from number to quantity and back. *Review of Educational Research*, *68*(4), 413–449.

Kata, A. (2012). Anti-vaccine activists, Web 2.0, and the postmodern paradigm - An overview of tactics and tropes used online by the anti-vaccination movement. *Vaccine*, *30*(25), 3778–3789.

Kortum, P., Edwards, C., & Richards-Kortum, R. (2008). The impact of inaccurate Internet health information in a secondary school learning environment. *Journal of Medical Internet Research*, *10*(2).

Lewandowsky, S., Ecker, U. K., Seifert, C. M., Schwarz, N., & Cook, J. (2012). Misinformation and its correction: Continued influence and successful debiasing. *Psychological Science in the Public Interest, 13*(3), 106-131.

Lombardi, D., Sinatra, G. M., & Nussbaum, E. M. (2013). Plausibility reappraisals and shifts in middle school students' climate change conceptions. *Learning and Instruction*, *27*, 50–62.

Lombardi, D., Nussbaum, E. M., & Sinatra, G. M. (2016). Plausibility judgments in conceptual change and epistemic cognition. *Educational Psychologist, 51*(1), 35–56.

May, D. K. (2009). *Mathematics self-efficacy and anxiety questionnaire.* (Doctoral dissertation, University of Georgia).

Murnane, R. J., & Willett, J. B. (2010). *Methods matter: Improving causal inference in educational and social science research.* Oxford University Press.

Murphy, P. K., & L. Mason. (2006). Changing knowledge and beliefs. In *Handbook of educational psychology* (Vol. 2nd, pp. 511–544). Mahwah, NJ: Lawrence Erlbaum Associates.

Pintrich, P., Marx, R., & Boyle, R. (1993). Beyond cold conceptual change. *Review of Educational Research, 63*(2), 167--199.

Ramirez, G., Shaw, S. T., & Maloney, E. A. (2018). Math anxiety: Past research, promising interventions, and a new interpretation framework. *Educational Psychologist, 15*(20), 1–20.

Ranney, M. A., Shonman, M., Fricke, K., Lamprey, L. N., & Kumar, P. (2019). Information that boosts normative global warming acceptance without polarization: Toward JS Mill's political ethology of national character. In D. Wilkenfeld & R. Samuels (Eds.) Anthology on the experimental philosophy of science (pp. 61-96). (In Bloomsbury's Advances in Experimental Philosophy series).

Ranney, M. A., & Clark, D. (2016). Climate change conceptual change: Scientific information can transform attitudes. *Topics in Cognitive Science*, *8*(1), 49–75.

Reys, R. E., & Reys, B. J. (2004). Estimation in the mathematics curriculum: A progress report. In *Beyond written computation* (pp. 101–112). Mathematics, Science & Technology Education Centre, Edith Cowan University.

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA). *Journal of Statistical Software, 48*(2), 1-36.

Sandoval, W. A., Greene, J. A., & Bråten, I. (2016). Understanding and promoting thinking about knowledge. *Review of Research in Education*, *40*(1), 457–496. https://doi.org/10.3102/0091732X16669319

Scheufele, D. A., & Krause, N. M. (2019). Science audiences, misinformation, and fake news. *Proceedings of the*

National Academy of Sciences, *116*(16), 7662–7669.

Sinatra, G. M. (2005). The "warming trend" in conceptual change research: The legacy of Paul R. Pintrich. *Educational Psychologist, 40*(2), 107–115.

Sinatra, G., & Seyranian, V. (2016). Warm change about hot topics. In L. Corno & E. Anderman (Eds.), *APA handbook of educational psychology* (pp. 245–256). Washington, DC: APA Publications.

Sowder, J. T., & Wheeler, M. M. (1989). The development of concepts and strategies used in computational estimation. *Journal for Research in Mathematics Education*, 130–146.

Stanovich, K. E., & West, R. F. (1997). Reasoning independently of prior belief and individual differences in actively open-minded thinking. *Journal of Educational Psychology, 89*(2), 342–357.

Thacker, I. (2020). *The Influence of Numerical Estimation Skills and Epistemic Cognition in Plausibility Judgments and Conceptual Change.* (Unpublished doctoral dissertation). University of Southern California, Los Angeles, CA.

Wilcox, R. (2017). *Modern statistics for the social and behavioral sciences: A practical introduction* (2nd ed.). Boca Raton, FL: CRC press.

Yarnall, L., & Ranney, M. A. (2017). Fostering scientific and numerate practices in journalism to support rapid public learning. *Numeracy, 10*(1), Article 3.