Supporting Climate Change Understanding With Novel Data, Estimation Instruction, and Epistemic Prompts

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Abstract

Texts presenting novel numerical data can shift learners' attitudes and conceptions about controversial science topics. However, little 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 data: numerical estimation skills and epistemic cognition. This research investigated combinations of two treatments—a numerical estimation and epistemic cognition intervention—that were designed to enhance people's ability to make sense of key numbers about climate change when integrated into an existing intervention. Results indicated that undergraduate students ($N = 516$) who engaged with climate change data held fewer misconceptions compared to a group that read an expository text, though their judgments of climate change plausibility were similar. Results also showed that the two modifications to the central intervention did not have statistically significant effects on knowledge or plausibility when compared with the unmodified intervention. However, we found that individuals' openness to reason with and integrate new evidence significantly moderated the knowledge effects of the intervention when the intervention was supplemented with both modifications. These findings provide emerging evidence that, among those who are open to reason with new evidence, supporting mathematical reasoning skills and reflection on discrepant information can enhance conceptual change in science.

Keywords: conceptual change, epistemic cognition, numerical estimation, plausibility judgments

Educational Impact and Implications Statement

Individuals are often exposed to data about scientific topics in news and information read online. This study advances the idea that presenting people with novel scientific data after they estimate those quantities can be a catalyst for scientific learning. We found that encouraging estimation and reflection on those estimates reduced misconceptions about climate change for individuals who were predisposed to be open minded to new evidence. Findings suggest that novel data supports learning, and that dispositions toward reasoning play an important role in whether individuals gain from estimation instruction and active reflection.

Supporting Climate Change Understanding With Novel Data, Estimation Instruction, and Epistemic Prompts

Misconceptions about controversial science topics are widespread. For example, as of 2020, only 55% of adults in the USA correctly believe that most scientists think that climate change is happening, meaning that the remaining 45% hold a serious misconception (Marlon et al., 2020). Fortunately, there are several approaches that exist to shift these misconceptions.

Numerical data found in the news or online can be a powerful tool for changing minds about relevant science topics. For example, we encourage you to take a moment to estimate in your head the following quantity: What is the percentage change in the world's ocean ice cover since 1960? While you may or may not be surprised at the true value (see footnote),[1] presentation of novel data in this way can elicit explicit reflection on the meaning of novel evidence and integration of supported claims. In this way, prompting people to estimate just a handful of numbers about climate change before presenting them with the actual values can shift their attitudes, beliefs, and misconceptions to be more aligned with scientists (Ranney & Clark, 2016). This instructional technique can shift people's attitudes, beliefs, and conceptions to be more aligned with scientists (Ranney & Clark, 2016; Rinne et al., 2006), suggesting that numerical data can be used as a catalyst for conceptual change. However, despite the benefits of this intervention, the mechanisms that underlie this change process remain understudied.

We propose that numerical estimation skills and epistemic cognition (active reflection on what is known) may be important mechanisms. To initially estimate a "real-world" quantity, a skilled learner might draw from their prior knowledge, make use of known quantities, and mathematically manipulate them to arrive at their estimate (e.g., Reys & Reys, 2004; Siegler,

[1] The change in world's ocean ice cover since 1960 is a 40% decrease (Ranney & Clark, 2016).

2016). An explicitly crafted estimate of this sort might better prepare the learner to interpret and assess the validity of a scientifically accepted value when later presented with it (c.f., Lombardi, Nussbaum, et al., 2016; Richter & Maier, 2017). Furthermore, if learners are explicitly prompted to reflect on differences between their estimate and the true value, such explicit evaluations might lead them to reconsider the plausibility of associated claims, and potentially revise their pre-existing conceptions (Lombardi, Nussbaum, et al., 2016). In this way, numerical estimation skill and reflection on what is known (epistemic cognition) might be two important mechanisms involved in conceptual change from novel data.

The purpose of this study was to develop a set of interventions that investigate mechanisms that may underlie the learning that occurs when people encounter novel data. Namely, we draw from theory on plausibility judgments for conceptual change (Lombardi, Nussbaum et al., 2016), and epistemic cognition (active reflection on whether information is true or justified; Chinn et al., 2014) to examine the impact of two mechanisms of conceptual change when learning from real-world numbers—numerical estimation skills and epistemic cognition. To accomplish this, we created two micro-interventions to modify an existing intervention, and then investigated four combinations of these two modifications and compared their effects to a comparison group that read an expository text. We also investigated whether emotional, motivational, and dispositional factors would moderate the effects of these interventions.

Theoretical Framework

Conceptual Change and Plausibility Judgments

When individuals encounter numerical data that conflict with their prior conceptions, conceptual change may occur. Conceptual change represents learning that occurs when new information conflicts with a learners' background knowledge, and conceptual knowledge is changed in some fashion (Dole & Sinatra 1998; Murphy & Mason, 2006). Researchers describe conceptual knowledge as either consistent or inconsistent with scientific explanations and thus, may define conceptual change as a reduction in scientifically inaccurate conceptions, or *misconceptions*. There are many definitions and operationalizations of conceptual change. Here, we consider the shifting of conceptual knowledge to be more aligned with scientific conceptions and less aligned with misconceptions to be conceptual change (Dole & Sinatra, 1998). For example, if a person holds the misconception that there is no scientific consensus that humans are contributing to 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 understanding and shift their conceptions about the scientific view. In this way, the meaning communicated by even a single number has the potential to prompt conceptual change (i.e., which we operationalize as greater alignment with scientific explanations and less with the misconception; Ranney & Clark, 2016). Conceptual change can be viewed as a process that is contingent upon characteristics of the information, such as its coherence and characteristics of the learner, such as their motivation, emotion, and attitudes (also called *warm constructs*; Dole & Sinatra, 1998; Pintrich et al., 1993; Sinatra, 2005; Sinatra & Seyranian, 2016).

Conceptual Change

Dole and Sinatra's (1998) Cognitive Reconstruction of Knowledge Model (CRKM) discerns between characteristics of the learner and those of the "message" (e.g., learning materials). These characteristics shape whether the learner will engage with the message and subsequently shift their conceptions to be more aligned with the scientific consensus (i.e., undergo conceptual change). *Learner characteristics* include the strength and coherence of an existing conception along with the learners' commitment to it; and epistemic motives and dispositions—inclinations toward a particular view of knowledge, such as a need for closure, openness to understand novel arguments, and dissatisfaction with current understanding. *message characteristics* refer to the learners' perceptions of information as: coherent, comprehensible, and compelling, and the claims supported by that information as being *plausible*. For example, an individual that encounters novel climate change data might shift their conception depending on: characteristics of the information (if it is coherent, comprehensible, compelling), plausibility of the claims supported by that novel information, and their cognitive and motivational state (e.g., if they find their conception dissatisfactory in light of the new data).

Plausibility Judgments for Conceptual Change

For individuals to change their mind about climate change based on novel data, they must first judge the information to be valid and the claims to be plausible. Plausibility can be defined as a tentative perception of the potential truth of a claim and plays an important role in conceptual change. The Plausibility Judgments for Conceptual Change (PJCC) model posits that novel information can incite conceptual change because it prompts learners to appraise or reappraise the plausibility of their existing beliefs and potentially correct misconceptions (Lombardi, Nussbaum, et al., 2016; this process is illustrated in Figure 1).

[INSERT FIGURE 1 AROUND HERE]

Individuals first *preprocess* information for validity prior to forming a plausibility judgment. Building from earlier models of plausibility, Lombardi's model posits that views of source validity depend on perceptions of corroboration and complexity of evidence, perceived conjecture, perceptions of source credibility, and heuristic rules and biases (Connell & Keane, 2006; Rescher, 1976). For example, preprocessing may involve numerical estimation heuristics employed by the learner to process the validity of numerical answers to math problems (e.g., Aljami & Reys, 2009; LeMaire & Fayol, 1995; Siegler, 2016). In such a way, we expected that estimation skills would support processing of novel data. The Two Step-Model of validation (Richter & Maier, 2017) adds nuance to the idea of processing source validity. The model posits that people validate information either routinely (Step 1) by relying on implicit plausibility judgments of belief-consistent information, or (Step 2) by elaborating on belief-inconsistent information. Such elaboration involves greater attention, working memory, integration of background knowledge, and can be activated by specific goals or epistemic motives. Findings from a systematic review of the literature show that belief-inconsistent information tends to receive less attention than belief-consistent information when individuals engage with texts that do not agree with their prior beliefs (Richter & Maier, 2017). However, elaboration and deeper processing of belief-inconsistent information can be improved with prompts to elaborate on inconsistencies, inclusion of rationales for activities, and are moderated by reader characteristics (e.g., beliefs about incorporating new evidence).

After preprocessing information for validity, a *plausibility judgment* of the claims supported by the evidence is made either via implicit or explicit processing (Lombardi, Nussbaum, et al., 2016). The extent to which an individual engages explicit processing to evaluate plausibility depends on motivational factors (e.g., interest or self-efficacy), topic emotions (e.g., mathematics anxiety), and "epistemic dispositions and motives" (e.g., the learners' openness to reason with new evidence). Explanations that are perceived to be more plausible than alternatives have greater *potential for conceptual change* (Lombardi, Nussbaum, et al., 2016; Dole & Sinatra, 1998). When a learner views an explanation as less plausible than their background knowledge, they are more likely to maintain their existing conception. In contrast, explanations perceived to be more plausible than prior conceptions have strong potential for conceptual change, though change is not guaranteed. For example, a student that encounters compelling climate change data may come to perceive the human induced climate change hypothesis as plausible, but may have an overriding commitment to their previous conception based on social group membership (Dole & Sinatra, 1998). However, with new evidence or contextual prompts, these plausibility judgments can be revisited and reappraised with more explicit levels of evaluation and greater potential for conceptual change. For example, a reappraisal cue might be a prompt for learners to explicitly consider novel climate change numbers in comparison with their own estimates. Such *plausibility reappraisals* are thought to be particularly important for conceptual change about controversial science topics where there may exist a "plausibility gap" between what scientists and what laypeople perceive as plausible (Lombardi & Sinatra, 2013).

Empirical research in the domain of science education has found strong links between perceptions of plausibility and conceptual change. Lombardi and Sinatra (2012) found that undergraduate students in a science course devoted to the topic of climate change had fewer misconceptions about deep-time and found human induced climate change to be more plausible compared with students in a typical intro-science course. In a follow up study, Lombardi, Danielson, and Young (2016) experimentally tested whether prompting undergraduate students to reflect on their own climate change knowledge would promote plausibility reappraisals. They found that students assigned to read a text that prompted reflection on their misconceptions rated scientific explanations of climate change as more plausible ($d = 0.43$) and had fewer misconceptions ($d = 0.47$) at posttest compared to students who read an expository text.

Theory and evidence also suggest that motivation, emotion, and epistemic dispositions are associated with plausibility judgments and conceptual change outcomes (e.g., Dole &

Sinatra, 1998; Lombardi, Nussbaum, et al., 2016; Lombardi & Sinatra, 2013; Sinatra, 2005). Lombardi and Sinatra (2013) found that teachers' initial plausibility judgments related to climate change were associated with their topic emotions (emotions that relate specifically to the topic of instruction) and epistemic motives (motivation related to goals and dispositions toward knowledge, such as "need for closure"). The authors found that teachers' anger towards teaching climate change and their need for closure both negatively and significantly predicted plausibility perceptions of human induced climate change. Thus emotions, motivation, and dispositions play a role in how plausibility judgments are formed and may help explain how people learn from numerical data.

Numerical Estimation

How do people make sense of and learn from novel policy-relevant quantities? Research on number concept, magnitude knowledge, and numerical estimation might help identify mathematical skills that are useful for individuals to make sense of numerical information (Case & Sowder, 1990; Dehaene, 2011; McIntosh et al., 1992; McIntosh & Sparrow, 2004; Siegler, 2016; Sowder, 1992; Sowder & Wheeler, 1989). Number concept (or "number sense") can be defined as a person's understanding of quantities and operations and involves many skills that are particularly useful for interpreting and making meaning out of numbers found in day-to-day experience (Dehaene, 2011; Mcintosh et al., 1992). Understanding and estimating magnitudes of quantities and drawing meaning from them is considered to be central to the development of number concept (Siegler, 2016) and is a particularly important skill in science, thus comprising an important intersection between mathematics and science K-12 standards (Cheuk, 2012). For the purpose of understanding how individuals interpret numbers about climate change, we focus our research on a domain of number concept that is often employed in informal settings and considered useful for plausibility judgments and conceptual change: numerical estimation.

Numerical estimation can be defined as an educated guess for a quantity that potentially draws from an individual's understanding of number, operations, and prior experiences (Dowker, 2005). Numerical estimation is used as a central indicator of numerical and cognitive development (e.g., Siegler, 2016), is reflected in the Common Core State Standards (CCSS, 2012). Adults and children who consistently make accurate estimations also tend to have good mathematical conceptual understandings and arithmetic skills (LeFevre et al., 1993; Park & Brannon, 2013; 2014; Booth & Siegler, 2008), greater working memory (Case & Sowder, 1990; Friso-van den Bos et al., 2013; Hecht & Vagi, 2010), and higher standardized test scores in mathematics (Booth & Siegler, 2006; Sasanguie et al., 2012; Siegler & Booth, 2004).

Estimation skills are traditionally divided into three categories: (a) computational estimation (estimates of computational problems), (b) numerosity (estimates based on sensory perception), and (c) measurement estimation (Reys & Reys, 2004; Sowder, 1992), the latter of which is most relevant for this study. Namely, measurement estimation concerns the explicit estimation of real-world measures (Bright, 1976; Joram et al., 2005; Sowder & Wheeler, 1989) and is useful for understanding factors that help people judge whether real-world quantities are valid and reasonable. Findings suggest that peoples' estimation accuracy and judgments of reasonableness improve when they use measurement estimation strategies. Measurement estimation skills may therefore support learners' comprehension and evaluation of given real-world quantities. For this study we created an intervention to support learners' use of the benchmark strategy—a tool for building associations and analogies—in order to impact the depth to which they draw meaning from numbers about climate change.

Analogies, Associations, and the Benchmark Strategy

Estimation accuracy and number concept improve as people make associations and analogies between symbolic notation and non-symbolic referents. The Integrated Theory of Numerical development (Siegler, 2016) proposes that numerical understanding and numerical estimation accuracy develop as individuals come to represent non-symbolic magnitudes and connect them to symbolic representations of magnitude. Two central mechanisms in facilitating this process are establishing *associations* of numerical symbols with non-symbolic referents (such as associating numbers with objects, gestures, or other phenomena) and mapping representations to one another by *analogy* (e.g., extending knowledge of one mathematical system or representation to another).

An example of analogy and association is when people extend their understanding of known numbers to estimate unknown numbers. This strategy has been termed 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; Dowker, 2005; Joram et al., 1998; Joram et al., 2005). The use of benchmark values in estimation is thought to involve (1) creating a "mental image" of some benchmark quantity like a standard unit of measurement, and (2) comparing it with the quantity to be estimated (e.g., by scaling the value using "unit iteration;" Joram et al., 2005). For example, when estimating the mass of *global* CO_2 emissions in 2014, it might be helpful to first know that the *USA* emitted about 5 gigatons of CO_2 that same year (Quéré et al., 2016). Given this benchmark quantity, one can then scale the value by a factor that they find plausible to estimate the unknown quantity. Lab-based experiments with undergraduate students suggest that exposure to benchmark values can improve the accuracy of estimates of distances between two cities (Brown & Siegler, 2001), other everyday quantities (Brown & Siegler, 1993, 1996, Friedman & Brown, 2000, Joram et al., 2005), and quantities specifically regarding climate change (Ranney & Clark, 2016). As such, benchmark strategies have immediate educational implications in that teaching students a small number of relevant facts can greatly improve their measurement estimations and judgments of plausibility.

However, mere exposure to benchmark values does not guarantee that individuals will apply benchmark strategies in relevant situations. Hildreth (1983) found that college freshman and elementary students do not spontaneously employ benchmark strategies or similar strategies very often to solve measurement estimation problems. However, direct instruction with worked examples on how and when to use benchmark strategies can increase frequency of strategy use and improve estimation accuracy (Hildreth, 1983; Joram et al., 2005). Thus, it is not only important for individuals to be given benchmarks required to make good estimates and identify plausible values, but they should also be given instruction regarding how and when to apply those skills. Yet, despite research showing that numerical estimation is an important aspect of number development and competency in mathematics and science, and that development can be supported by emphasizing associative/analogical processes such as the benchmark strategy, there is very little research on how these processes might support learning from policy-relevant data.

Epistemic Cognition

Another skill that is thought to contribute to improved plausibility judgments and conceptual change is that of *epistemic cognition*—the thinking that people do about knowledge and knowing (Chinn, et al., 2014; Greene et al., 2016; Sandoval et al., 2016). Epistemic cognition is hypothesized to predict the extent to which learners evaluate the plausibility of a claim in light of new information, leading to greater potential for conceptual change (Lombardi, Nussbaum, et al., 2016). There are multiple models of epistemic cognition (for a review, see Greene et al., 2016), in this section we review two framings that are relevant to this study—epistemic dispositions (which focus on stable, trait-level beliefs about the nature of knowledge and knowing) and a more dynamic and context sensitive view of epistemic cognition.

Epistemic Dispositions

Epistemic dispositions refer to an individual's relatively stable perspectives about knowledge and knowing and are expected to moderate conceptual change outcomes. Theory predicts that constructivist epistemic dispositions prepare people to more explicitly evaluate novel information and integrate implicated claims into their existing belief structures (Lombardi, Nussbaum, et al, 2016). For example, undergraduate students' and adults' openness to evaluate novel evidence and willingness to revise their existing beliefs, as captured using a seven-item questionnaire called the "Active Open-Minded Thinking" scale, has been shown to highly correlate with their ability to evaluate the validity of and learn from novel arguments (e.g., Stanovich & Toplac, 2019; Stanovich & West, 1997). Active open-minded thinking is also considered to be a focal epistemic disposition when engaging in probabilistic and statistical reasoning (Stanovich, 2013). People with higher levels of active open-minded thinking might be expected to more explicitly evaluate novel, belief-inconsistent information when prompted to do so, rather than attending to information consistent with their prior beliefs (Richter & Maier, 2017). Such explicit processing is linked with more thoughtful plausibility judgments and greater potential for conceptual change (Lombardi, Nussbaum, et al., 2016). Based on this theory and evidence, constructivist epistemic dispositions might be expected to moderate the effects of interventions that present novel data, especially among interventions that explicitly prompt reflection on belief-discrepant information.

A Context-Sensitive View of Epistemic Cognition

Other perspectives view epistemic cognition as a dynamic process that is sensitive to context, involves motivational variables such as aims and goals, and relies on schema that develop over time (Chinn et al., 2014; Sinatra, 2016). For example, according to the AIR model, epistemic cognition is a situated process that relies on individuals' *A*ims (goals and associated values of goals), *I*deals (espoused standards for achieving epistemic aims), and *R*eliable processes for knowing (schemas for producing true, justified beliefs; Chinn et al., 2014). For example, when people read a text, they may not always seek truth or justification from the text that they encounter (an epistemic aim) but may instead be reading for pleasure or memorization (both non-epistemic aims). We created an intervention intended to activate learners' epistemic aims by asking participants to reflect on their knowledge and articulate whether discrepancies between their initial estimates and the true value changed their ideas about climate change (see Appendix I). We expected that such prompts would encourage people to slow down and reflect on their own understanding in light of new data and that such reflection would prompt re-evaluation of their conceptions.

Though the approach of activating epistemic aims is relatively new, there is some evidence that shorter, single session interventions can be effective at shifting epistemic aims. For example, a recent study by Hendriks et al. (2021) made use of an experimental manipulation using slightly different instructions in a survey that seemed to successfully shift the epistemic aims of pre-service teachers in Germany to either attend to theoretical explanations or attend to practical advice from a text (Hendriks et al., 2021). The manipulation revealed significant differences in perceived expertise, integrity, and benevolence of the expert who had written the text. Yet, while research has explored the effects of manipulating epistemic aims on perceived credibility and validity of a text source, little research has explored their effects on plausibility evaluations and conceptual change. Further, little research has sought to investigate whether such prompts are effective when individuals learn from numerical data about climate change. As such, we designed an intervention intended to activate epistemic aims and improve explicit evaluation of data and readiness to apply mathematical principles to interpret climate change numbers.

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 et al., 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 *E*stimate quantities, state a *P*reference for what they would like the quantity to be, *I*ncorporate the answer, and then *C*hange 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 other words, studies in this paradigm measure learning and conceptual change in terms of changes in individuals' policy preferences. However, despite many studies demonstrating that variations on EPIC interventions lead individuals to shift their policy preferences regarding climate change, the question remains as to whether EPIC can shift explicitly stated scientific misconceptions and plausibility perceptions of scientifically accepted claims. Furthermore, prior EPIC studies provide little information regarding the validity and reliability of conceptual change scales. This raises another question as to whether conceptual changes that occur as a result of an EPIC intervention focused on climate change might also be detected when using valid and reliable measures for capturing climate change knowledge.

Potential Moderators

Few studies have explored moderating effects of emotions, motivation, and epistemic dispositions when people learn from novel data. In this section, we argue that mathematics anxiety, self-efficacy, and epistemic dispositions may be important moderators in this learning process.

Mathematics Self-Efficacy and Mathematics Anxiety

Mathematics self-efficacy is defined as individuals' beliefs or perceptions regarding their abilities in mathematics (Bandura, 1997), and is linked with motivation to learn, persistence on challenging tasks, and academic achievement (Pajares & Graham, 1999; Zeldin et al., 2008). For example, findings suggest that mathematics self-efficacy is strongly associated with college students' mathematics achievement (Hall & Ponton, 2005; Higbee & Thomas, 1999).

Mathematics anxiety can be defined as "feelings of tension and anxiety that interfere with the manipulation of numbers and the solving of mathematical problems in a wide variety of ordinary life and academic situations" (Richardson & Suinn, 1972; p.551). Mathematics anxiety, while representing only one of many possible emotional constructs that might be relevant in learning situations (c.f. Muis et al., 2018), was chosen because it might interfere with mathematical aspects of student learning; it is associated with college students' negative attitudes and emotions toward mathematics (Jackson & Leffingwell, 1999) and decreased level of mathematical achievement and computational fluency (Cates & Rhymer, 2003).

Findings from research on mathematics self-efficacy and mathematics anxiety is consistent with plausibility judgments in conceptual change research. The Plausibility Judgments for Conceptual Change model assumes that motivation and emotion shape the degree to which individuals critically engage with learning material (Lombardi, Nussbaum, et al, 2016). Negative emotions and motivational states—like mathematics anxiety and low mathematics self-efficacy—impede focus, bear on working memory (e.g., Ramirez et al, 2018), and may potentially interfere with explicit evaluations of belief-inconsistent arguments and decrease the likelihood of conceptual change (Lombardi, Nussbaum, et al., 2016). Therefore, we expected that participants with higher levels of mathematics anxiety and low levels of mathematics self-efficacy will be less likely to deeply engage in mathematical thinking when presented with numerical estimation instruction and during estimation tasks.

Epistemic Dispositions

As previously noted, theory posits that epistemic dispositions are linked to explicit plausibility judgments and higher potential for conceptual change (Lombardi, Nussbaum, et al., 2016). Specifically, active open-minded thinking—openness to evaluate novel evidence and revise existing beliefs—is an epistemic disposition that is associated with explicit evaluations of novel arguments (e.g., Stanovich & Toplac, 2019; Stanovich & West, 1997). For this reason, we expected that active open-minded thinking would moderate the learning effects of the EPIC intervention, especially among conditions that explicitly prompted participants to compare their understanding with new evidence.

Current Study

In sum, we contend that in order for learners to attend to and learn from novel information, they must develop the estimation skills necessary to accurately evaluate data that they encounter as well as the skills to evaluate epistemic aspects that information. That is, they must learn numerical estimation skills and the skills associated with epistemic cognition. Currently, there is no empirical research that we could find that investigates the role of estimation skills and epistemic cognition in conceptual change processes. Further, there is little research investigating applications of numerical estimation skills to support learning of socio-scientific topics. For the current study, we created variants of an intervention that presents people with novel data about climate change by modifying the intervention to experimentally manipulate either estimation skill, epistemic cognition, both, or neither. This combination of modifications was intended to improve people's readiness to apply mathematical principles for comparing and interpreting climate change numbers, as well as to prompt explicit evaluations of belief-inconsistent data. Our research is guided by five questions:

1. To what extent does estimation of and exposure to novel climate change data (i.e., an adapted version of the EPIC intervention) improve learners' (a) knowledge of climate change and (b) plausibility judgments compared with reading an expository text?
2. To what extent does enhancing this intervention with instruction on estimation strategies change learners' (a) knowledge and (b) plausibility judgments of climate change?
3. To what extent does enhancing this intervention with prompts to activate epistemic aims change learners' (a) knowledge and (b) plausibility judgments of climate change?
4. Is there an interaction between the effects of the estimation skills and epistemic aims modifications on (a) knowledge and/or (b) plausibility judgments of climate change?

5. To what extent do mathematics anxiety, mathematics self-efficacy, and epistemic dispositions moderate the effects of the intervention and variants on knowledge, plausibility, and estimation skill?

Hypotheses

Based on prior research (Lombardi, Nussbaum, et al., 2016; Ranney & Clark, 2016), we first hypothesized that undergraduate students assigned to the EPIC intervention conditions would have (H1a) greater climate change knowledge and (H1b) perceive the human induced climate change hypothesis to be more plausible when compared with the comparison group. Such findings would partly reproduce results of Ranney and Clark (2016) and support the Plausibility Judgments for Conceptual Change model (Lombardi, Nussbaum, et al., 2016). Second, we hypothesized that supplementing the EPIC intervention with instruction on estimation skills would lead to (H2a) greater knowledge and (H2b) heightened plausibility perceptions compared with EPIC conditions that did not include estimation instruction. These hypotheses were drawn from the Plausibility Judgments for Conceptual Change model which suggests that prompting validity processing heuristics would potentially lead to higher levels of explicit evaluation of plausibility (Lombardi, Nussbaum, et al., 2016). Third, we hypothesized that EPIC modified with prompts to activate epistemic aims would predict (H3a) better knowledge outcomes and (H3b) greater perceptions of plausibility in the human induced climate change hypothesis compared with EPIC conditions that were unmodified. We made this prediction because prompts intended to activate undergraduate students' epistemic aims are expected to lead to more explicit evaluations of information (Chinn et al., 2014) and predict more explicit plausibility judgments and greater conceptual change, as hypothesized by the

Plausibility Judgments for Conceptual Change model. Fourth, we predicted that improving both students' estimation skills and epistemic cognition would predict the best (H4a) knowledge outcomes and (H4b) plausibility perceptions. As predicted by Lombardi and colleagues, (2016) we anticipated that leveraging data-processing heuristics and explicit reflection on the arguments supported by the data would lead to the greatest conceptual change. We had no specific hypotheses for our fifth research question, which was exploratory.

Methods

To answer our research questions, we formed a national Qualtrics panel of undergraduate students to participate in an experimental online survey. Qualtrics, a third-party vendor, distributed email invitations and a total of 2,856 responses were recorded, 2,187 (67%) of them were not eligible to participate in the study because they were not a full-time undergraduate student or were under 18 years, and 153 (7%) were not included in analyses because they either did not pass an attention check at the beginning of the survey or they were flagged as a "speeder" based on an algorithm used by Qualtrics (see Supplementary Materials for details). The remaining 516 (18%) of participants fully completed the survey and were retained as the full analytic sample. There was no missing data. We ran a post-hoc sensitivity analysis using GPower to assess the minimum detectable effect for our most demanding hypothesis with respect to sample size, which revealed that we were able to detect an effect size of 0.153 for a five-group ANCOVA with power of .8 and alpha level of .05 (Erdfelder et al., 1996). Additional methodological details and results are provided in the Supplementary Materials. Study materials, data, and analysis syntax are available at https://bit.ly/3xcBjUQ.

Participants' median reported age was 20 years, and 81% identified as Female, 16% Male, 2% reported their gender as "Other" or "Prefer not to say," 64% White, 11% African

American, 9% Asian, 9% Hispanic, and 43% as either Liberal or Very Liberal. We sampled from multiple locations across the United States to obtain a sample that is representative of the general public regarding their baseline beliefs about climate change (i.e., 70% agreed or strongly agreed that "Earth's climate is currently changing"; for details, see Supplemental Materials, Sampling Strategy). 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 comparison group and combinations of two interventions (see below), and (c) completed an identical post-test of knowledge and a demographics questionnaire.

Outcome Measures

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, hereafter referred to as "the knowledge measure;" Lombardi et al., 2013; see Supplemental Materials, Appendix A). Construct and content validity of the abbreviated scale was established through pilot studies and cognitive interviews. The knowledge questionnaire was given to participants just prior to and immediately after instruction and was intended to measure participants' conceptions about the scientific consensus on human-induced climate change and items were selected to align with information presented in the EPIC intervention. For example, participants rated to what extent climate *scientists* agree with statements such as, "greenhouse gas levels are increasing in the atmosphere" on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). Agreement with such a statement reflects a correct, verifiable conception about the scientific consensus, while disagreement represents a misconception. As such, knowledge shifts are thought to represent changes in misconceptions regarding what scientists endorse. Note that such knowledge of scientific consensus is different from, but related to, personal acceptance of climate change (e.g., Hornsey et al., 2016; Lewandowsky et al., 2013). The measure at pre and posttest was reliable at conventional levels (Cronbach's alpha = .68 at pretest, .83 at posttest; McDonald's omega = .72 at pretest, .84 at posttest).

Plausibility Judgments

Plausibility judgments comprised the second primary outcome variable in this study and were captured using the plausibility perceptions measure (PPM; Lombardi & Sinatra, 2012; see Supplemental Materials, Appendix B). The plausibility perceptions measure is an instrument that consists of eight items that prompt participants to report the plausibility of the claim that human activity is responsible for climate change. For example, participants reported their perceived plausibility of the claim that, "Human caused global warming will lead to some impacts that are abrupt or irreversible, such as massive polar ice melt" and rated the plausibility on a scale from 1 (*greatly implausible or even impossible*) to 10 (*highly plausible*). The items were originally taken from statements made by the Intergovernmental Panel on Climate Change (2007) and were modified to optimize readability (Lombard & Sinatra, 2012). For the current study, the plausibility perceptions measure was found to be reliable (Cronbach's alpha = .95 at pretest, .95 at posttest; McDonald's omega = .95 at pretest, .95 at posttest).

Distinctions between knowledge and plausibility. It is important to note distinctions between the knowledge and plausibility scales used in this study. Knowledge items prompted participants to state the extent to which climate scientists adhere to statements about climate change and could be confirmed as being more or less "correct," while the plausibility perceptions scale asked participants to report their personal stance regarding the plausibility of the human induced climate change hypothesis (Lombardi et al., 2013). For example, the knowledge items ask participants to rate whether they know that *scientists* view sea level rise as connected to climate change while the plausibility items ask participants to judge the extent to which *they (themselves)* find it plausible that human actions are contributing to sea level rise. In other words, the knowledge items measure conceptions of scientific consensus, which can be confirmed or disconfirmed with evidence, whereas plausibility perceptions cannot because they represent personal views of potential truth (see also Lombardi et al., 2013). Yet, we understand that the distinction between scientists' and personal perceptions may not have been salient to participants, and that both scales might have captured the same construct. To empirically test whether this subtle distinction was, in fact, captured by our knowledge and plausibility scales, we tested whether plausibility perceptions and climate change knowledge were distinguishable by comparing fit indices of one-factor and two-factor confirmatory factor analyses (CFA) at pretest and posttest. We found that the one-factor models generally had poor fit, while the two factor models had acceptable fit for both outcomes at pretest and posttest (for details, see the Confirmatory Factor Analysis Discerning Plausibility from Knowledge section in the Supplementary Materials). Findings generally confirm the distinctions between plausibility and knowledge are measurable.

Measurement Estimation Skills

Estimation skills were captured using a measurement estimation task adapted from (Munnich et al., 2008; see Supplemental Materials, Appendix C) wherein participants estimate two sets of nine real-world quantities (e.g., the median US age, teacher salary, soft-drink calories) once before and once after an intervention. Scoring for this measure was as follows:

three points for an answer within 10% of the correct answer, two points for an answer between 10% and 20%, one point for answers between 20% and 30% and zero points beyond 30% (see Hanson & Hogan, 2000; Hogan & Brezinski, 2003). The development of the scale persisted over several iterations of pilot tests (see "Development of Numerical Estimation Scale" in the Supplemental Materials), yet despite these efforts, the reliability of the estimation items with the undergraduate sample were not acceptable at traditional levels (Cronbach's alpha = .44 at pretest, .54 at posttest; McDonald's omega = .55 at pretest, .53 at posttest). The poor reliability of our scales as well as pre-existing measurement estimation scales (e.g., alpha = .52; Hogan & Brezinski, 2003) begin to suggest that measurement estimation skills may require multiple independent skills, are multidimensional, and do not load onto a single construct. Further, item-level statistics based on classic and Partial Credit Rasch models using the "pairwise" package in R (Heine, 2014) revealed disordered threshold values, suggesting that for many items, higher estimation scores did not correspond with higher levels of the underlying construct (de Ayala, 2009; for the full analysis, see the section, Item Response Theory (IRT) Models, in the Supplemental Materials).

Potential Moderators

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; see Supplemental Materials, Appendix D). The MSEAQ consists of 28 items that were 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 classic measures of mathematics anxiety (s-MARS) and mathematics self-efficacy (see May, 2009). In the current study, the instrument was shown to be reliable overall (Cronbach's alpha = .96; McDonald's alpha = .94), as were the two subscales for mathematics self-efficacy (Cronbach's alpha = .94; McDonald's alpha = .93) and mathematics anxiety (Cronbach's alpha = .93; McDonald's alpha = .96). Average scores for the two subscales were computed and used in moderation analyses.

Epistemic Dispositions

Baseline epistemic dispositions were measured using the Actively Open-Minded Thinking scale (AOT; Stanovich & West, 1997; see Supplemental Materials, Appendix E). The Active Open-Minded Thinking scale is a measure of epistemic dispositions 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*; Chronbach's alpha = .70; McDonald's alpha = .71). This measure was included in our analyses to observe whether epistemic dispositions moderate conceptual change outcomes, as inferred from the Plausibility Judgments for Conceptual Change model (Lombardi, Nussbaum, et al., 2016).

Interventions and Experimental Conditions

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

[INSERT FIGURE 2 AROUND HERE]

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 and Clark (2016) and asked participants to estimate mostly unitless proportions (e.g., "What is the change in the percentage of the world's ocean ice cover since the 1960s?"; also see Table 1 for examples, and Supplemental Materials, Appendix F for all items). The remaining six items were created by the authors 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 and Supplemental Materials, Appendix G for all items). Newly created items were intended to be more challenging and require a greater level of numerical estimation skills to accurately estimate—each quantity was presented with a benchmark value or "hint" in order to enable participants the opportunity to mathematically manipulate the benchmarks in order to better estimate the unknown values. Note that the goal of this measure was to assess the impact of novel statistics, not to assess people's estimation accuracy of climate change numbers. As such, students' actual estimates of climate change quantities were not used in this study.

[INSERT TABLE 1 AROUND HERE]

The estimation skills modification appeared before the EPIC intervention for those assigned to this condition. The 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 and were followed by two interactive examples (see Table 1 for an excerpt, see Supplemental Materials Appendix H for full intervention). The epistemic cognition modification consisted of two types of prompts intended to activate epistemic aims. The first was embedded in the instructions that appeared just before the EPIC task and notified participants that they would, "…be asked to reflect on the differences between your estimate and the true value in order to encourage you to reflect on your own understanding." The second was a set of prompts consisting of open answer text-boxes 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 and encourage people to slow down and reflect on their own understanding in light of new data (see Table 1 for a sample or Supplemental Materials, Appendix I for full intervention).

Participants who were assigned to the comparison group rather than EPIC or a modification to EPIC read an expository text to account for the time that they would have spent engaging in the intervention (see Supplemental Materials, Appendix J). Specifically, participants read an expository text called "The Enhanced Greenhouse Effect" created by Nussbaum and colleagues (2017) that explains how the greenhouse effect works and provides details regarding human contributions to the greenhouse effect. The full text is 817 words in length and has an 11th grade Flesch-Kincaid readability level.

Results

Preliminary Analyses

Preliminary analyses revealed no significant differences at pretest between conditions with regards to knowledge ($F = 1.07$, $p = .368$), plausibility judgments ($F = 0.58$, $p = .665$), estimation skill ($F = 0.60$, $p = .665$), and all moderating variables (all Fs < 1.54, all ps > .187). Skew ranged from -0.87 to 0.51 and kurtosis ranged from -0.46 to 0.56 for all outcome measures. Both are considered acceptable (Tabachnick & Fidell, 2013). Descriptive statistics for all main outcomes and predictor variables by condition are presented in Table 2 and intercorrelations among variables are shown in Table 3. All analyses were performed using R Version 3.6.1.

[INSERT TABLE 2 AND 3 AROUND HERE]

Notably, there were improvements in knowledge and plausibility perceptions from pre-test to posttest. Paired *t*-tests revealed significant improvements in knowledge ($t(412) = 7.96$, $p < .001$, $d = 0.31$) and plausibility perceptions ($t(412) = 3.17$, $p = .002$, $d = 0.11$) from pre-test to post-test for the intervention conditions combined. Students in the comparison group also significantly improved from pretest to posttest with regards to plausibility perceptions ($t(102) = 2.15$, $p = .034$, $d = 0.12$), but not with regards to knowledge ($t(102) = 1.45$, $p = .151$, $d = 0.10$). Figure 3 presents a visualization of the pretest and posttest means by condition.

[INSERT FIGURE 3 AROUND HERE]

Analytic Approach

To assess the magnitude of the effects of the EPIC intervention on knowledge compared with the control group (H1a) and relations among variants (H2a, H3a, H4a), we used an ANCOVA model testing four sets of planned contrasts with posttest knowledge as the outcome and prior knowledge as the covariate. The first contrast compared the four EPIC conditions with the comparison group (H1a). The remaining three contrasts included only the four variants of the EPIC conditions and compared mean posttest knowledge among students who were provided estimation instruction with those who were not (H2a), compared students who were provided epistemic cognition prompts with those who were not (H3a), and tested if there was an interaction between epistemic cognition prompts and estimation instruction (H4a; see Table 4 for contrast weights). These analyses were repeated with posttest plausibility judgments as the main outcome variable and prior plausibility judgments as the covariate (i.e., to test H1b, H2b, H3b, and H4b). Prior to all analyses, we confirmed that there were no significant interactions between condition and pretest knowledge (p = .379) and condition and pretest plausibility (p = .296), suggesting that our data met ANCOVA and regression assumptions (Murnane & Willett, 2010).

To explore whether motivational, emotional, or epistemic dispositional variables moderated the intervention effects (RQ5), we regressed knowledge, plausibility, and estimation skill outcomes on the condition to which students were assigned and included math anxiety, efficacy, or epistemic dispositions as a moderator in separate models, the interaction between the moderator and the condition assigned, and pretest scores as a covariate.

The Effects of EPIC and Variants on Climate Change Knowledge (H1a–H4a)

When posttest knowledge was the main outcome and prior knowledge was the covariate, we found a significant effect of the experimental conditions ($F(4,510) = 5.41$, $p < .001$, partial $\eta^2 = .019$). The first of the planned contrasts revealed significant improvement in posttest knowledge among people assigned to the EPIC conditions when compared with the comparison group (H1a; $t = 6.25$, $p = .002$, $r = .14$). Regarding the remaining knowledge contrasts, we found no statistically significant impact of the estimation intervention (H2a; $t = 0.50$, $p = .614$, $r = .02$), epistemic cognition prompts (H3a; $t = 0.565$, $p = .565$, $r = .03$), or interactions between them (H4a; $t = -0.005$, $p = .996$, $r < .01$). As such, we found support for our hypothesis (H1a) that EPIC interventions would improve knowledge revision, but did not find support for our hypotheses that variants of EPIC would contribute added knowledge benefits (H2a, H3a, H4a).

The Effects of EPIC and Variants on Plausibility Perceptions (H1b–H4b)

We then tested the same model with plausibility perceptions as the outcome and prior plausibility perceptions as the covariate, which revealed no significant effect of condition ($F(4,510) = 1.35$, $p = .25$, partial $\eta^2 = .009$). Planned contrasts revealed no statistically significant effect of the EPIC interventions compared with the comparison group (H1b; $t = 0.09$, $p = .932$, $r < .01$), no effect of the estimation intervention (H2b; $t = 1.61$, $p = .109$, $r = .07$), no effect of epistemic cognition prompts (H3b; $t = -1.26$, $p = .209$, $r = .06$), nor interactions between estimation instruction and epistemic cognition prompts (H4b; $t = 0.62$, $p = .535$, $r = .03$). As such, we found no support for our hypotheses that the EPIC intervention or variants improved plausibility perceptions (H1b, H2b, H3b, H4b).

[INSERT TABLE 4 AROUND HERE]

Moderators of Knowledge, Plausibility, and Estimation Skill (RQ5)

With regards to our fifth research question, we explored whether math anxiety, self-efficacy, or epistemic dispositions would moderate relations between treatment effects and conceptual change outcomes. Based on Lombardi, Nussbaum, et al's (2016) model positing that topic emotions, motivation, and epistemic dispositions are factors that predict more explicit plausibility judgments, and thus higher potential for conceptual change, we tested whether mathematics anxiety, mathematics self-efficacy, and active open-minded thinking moderated the effects of the EPIC intervention and its four variants in linear regression models. As such, we regressed knowledge, plausibility, and estimation skill outcomes on the condition to which students were assigned, the moderator (math anxiety, self-efficacy, or epistemic dispositions), the interaction between the moderator and the condition assigned and included pretest scores as a covariate. We used indicator variables to signify different variants of the EPIC conditions with the comparison condition as a reference category. We used robust heteroscedasticity-consistent standard error estimations and centered all continuous variables around the mean prior to analyses (e.g., Cohen et al., 2013).

When the outcome was posttest knowledge, we found that EPIC conditions significantly outperformed the comparison group (see Table 5 for all coefficients and *p*-values). We also found that active open-minded thinking was a significant predictor of posttest knowledge and moderated the effects of the EPIC intervention with both modifications, before and after including prior knowledge as a covariate. That is, the EPIC condition modified with both estimation instruction and epistemic cognition prompts had stronger effects among individuals with higher open-minded thinking. Compared with the control group, participants in the twice modified EPIC condition had 0.26 standard deviations more post-test knowledge than the comparison group, and these effects were stronger (0.48 standard deviations) for those with active open-minded thinking levels one standard deviation above the mean. No other moderating effects or main effects of math anxiety or self-efficacy on posttest knowledge were found.

[INSERT TABLE 5 AROUND HERE]

When the main outcome was posttest plausibility judgments, we found a significant and positive main effect of active open-minded thinking (see Table 6 for all coefficients and *p*-values). We also found that, despite finding no main effects of mathematics self-efficacy, it was a significant and positive moderator of posttest plausibility judgments, yet this finding was only significant after adjusting for prior plausibility. No additional main effects or moderation effects were found, before or after adjusting for prior plausibility.

[INSERT TABLE 6 AROUND HERE]

We also tested whether math anxiety, self-efficacy, or epistemic dispositions moderated the effect of the EPIC intervention variants on post-test estimation accuracy. Findings were mixed. Mathematics self-efficacy was found to significantly moderate the effects the EPIC intervention supplemented with both the estimation and epistemic cognition modifications when the outcome was post-test estimation skill (β = 0.26, *SE* = 0.13, *p* = .041), but not after adjusting for prior knowledge (*p* = .105). We also found that active open-minded thinking was a positive predictor of posttest estimation skill, before adjusting for prior estimation skill (β = 0.26, *SE* = 0.13, *p* = .041), but not after (*p* = .101), and there was a consistent moderating effect of open-minded thinking on the effects of the twice modified EPIC intervention before (β = 0.263, *SE* = 0.13, *p* = .050) and after (β = 0.259, *SE* = 0.12, *p* = .039) adjusting for prior estimation skill. We also found consistent negative effects of the EPIC intervention variants on posttest estimation skill. However, these findings should be interpreted with caution given that the estimation skill measure was not found to be reliable at conventional levels at either pretest or posttest, and there were serious issues with the how the partial credit scores bared out (i.e., disordered threshold values from partial credit Rasch models; see Supplemental Materials for a full report). As such, full results from this moderator analysis are presented in the Supplemental Materials to minimize the risk of spreading unwarranted conclusions (Table S2 in the Supplementary Materials for coefficients and *p*-values).

Discussion

Prior research suggests that just a handful of surprising numbers can shift people's conceptions about climate change. The current study attempted to recreate previous findings using a subset of items from a valid and reliable instrument to test specific misconceptions about climate change, and additionally focused on testing the impact of two supplementary interventions—one to support numerical estimation skills, and another to activate epistemic cognition—both designed to intensify the benefits of the learning that occurs when engaging with surprising data using the EPIC intervention. Here, we discuss the results and how they pertain to the Plausibility Judgments for Conceptual Change model.

Exposure to Surprising Numerical Data Can Support Conceptual Change

We found a significant effect of the EPIC intervention on undergraduate students' climate change knowledge. On average, the four EPIC groups performed about a third of a standard deviation better than the comparison group on the seven-item knowledge scale at posttest. Such evidence is consistent with prior findings that demonstrate the effectiveness of EPIC for climate change learning (e.g., Ranney & Clark, 2016), providing further support for the idea that exposure to novel numerical information about climate change can support conceptual change.

However, we found no significant impact of the EPIC intervention on climate change plausibility perceptions. One explanation for this may be that the expository text used as the comparison condition, while not effective at correcting specific misconceptions about climate change, was successful at shifting climate change plausibility perceptions from pretest to posttest ($d = 0.12$) at levels that were similar to the treatment groups ($d = 0.11$). While all conditions shifted plausibility judgments, only the EPIC interventions significantly shifted knowledge. This suggests that plausibility perceptions may be more malleable than misconceptions. Plausibility perceptions might be swayed by a convincing expository text while shifting misconceptions may require multiple encounters with belief-inconsistent information and nudges to inspire reappraisals, leading to the adoption of new conceptions (Lombardi, Nussbaum, et al., 2016).

No Overall Impact of an Estimation Strategies Intervention

We found no evidence that enhancing the EPIC intervention with numerical estimation instruction improved the effects of the EPIC intervention on climate change knowledge or plausibility perceptions overall. The estimation intervention itself was intended to promote use of measurement estimation strategies (Brown & Siegler, 2001; Dowker, 2005; Joram et al., 1998), elicit heightened levels of quantitative reasoning, and thus explicit validation checks and plausibility judgments of novel data (Lombardi, Nussbaum, et al., 2016; Richter & Maier, 2017). However, it may be the case that these strategies were naturally employed by all participants who estimated numbers, regardless of condition. Or it could be that an entirely different set of strategies may be important for interpreting the scientifically accepted values when presented. Future studies might look more carefully at the mathematical skills that individuals draw from when estimating and interpreting policy-relevant quantities, and whether these skills differ from estimates of policy-irrelevant measurements (e.g., length measures; Joram et al., 1998).

No Overall Impact of Prompts to Activate Epistemic Aims

Findings revealed that prompts to activate epistemic aims had no detectable effect on undergraduate students' climate change knowledge or plausibility perceptions overall. This may suggest that our modified intervention was not effective in prompting active reflection and elaboration on belief-inconsistent information (e.g., Lombardi, Nussbaum, et al., 2016; Richter & Maier, 2017) at levels above the baseline EPIC intervention. The intervention may have been ineffective because the prompts could have elicited non-epistemic reflections (e.g., on the effects of climate change), created fatigue among participants that outweighed any benefits, elicited reflection on existing understandings without integrating the given scientific evidence. Future research studies might use simpler, fewer, and more targeted reflection prompts that elicit reflection on more specific aspects of knowledge. Another explanation is that prompts to reflect on corrective information may have led some participants to double-down on their existing stance and increase resistance to persuasion. Though this effect, sometimes termed "the backfire effect," is rare (e.g., Jacobson et al., 2021), researchers should be aware of the possibility of provoking counterproductive reactance effects when designing interventions.

To date, efforts to design micro-interventions intended to shift short-term epistemic aims and long-term epistemic dispositions are only emerging. Although there is some evidence that short, single-session interventions can be effective at shifting epistemic beliefs or epistemic aims (see e.g., Cartiff et al., 2021; Kienhues, et al., 2016), much of this work was conducted in a very different setting than ours and, to our knowledge, none measured whether prompts to activate epistemic aims were associated with learning outcomes, which was the main goal of our research. Further, a recent metanalysis suggests that epistemic cognition interventions are not as effective with college-level populations when compared with adults or K-8 students (Cartiff et al., 2021), which may explain the small effects of our epistemic cognition intervention.

No Detected Interactions Between Epistemic Cognition and Estimation Skill Conditions

We found no significant interactions between intervention conditions, likely due to the very small effects of the estimation and epistemic cognition interventions. With improved intervention design, future research might explore whether such an interaction might occur.

Moderating Effects of Epistemic Dispositions

We found that epistemic dispositions significantly moderated conceptual change outcomes when learning from novel quantitative information, as predicted by the Plausibility Judgments for Conceptual Change model (Lombardi, Nussbaum, et al., 2016). Specifically, we found that open-minded epistemic dispositions were associated with climate change knowledge and plausibility, and moderated the effects of the twice modified EPIC condition on post-test knowledge. That is, individuals with higher levels of active open-minded thinking learned more about climate change when assigned to receive estimation instruction and prompts to activate epistemic cognition compared with those who did not. Openness to reason with novel evidence seems to prepare people to more explicitly consider the plausibility of novel information, help them transition from their existing knowledge base to even more knowledge, and supports receptivity to interventions that facilitate such knowledge revision. Specifically, when presented with tools to evaluate novel quantities *and* prompted to reflect on their knowledge discrepancies, individuals with higher levels of open-minded thinking may be better equipped to make use of quantitative skills when reflecting on novel evidence.

Our findings also suggest that the benefits of instruction to support estimation skills may face some epistemic barriers. The prior success of numeracy interventions highlights the important role of associating and analogizing between mathematical and non-symbolic knowledge (Siegler, 2016), however much of this prior research studies individuals estimating quantities with fairly neutral referents (e.g., the distance between two cities), which has important tradeoffs for learning. On the one hand, estimating more neutral quantities may pose fewer obstacles to learning mathematics because neutral quantities are likely to elicit fewer expectations and attitudes aligned with people's socio-political belief systems, which can interfere with learning (e.g., Authors, 2020). On the other hand, *only* engaging with neutral data can reinforce perceptions that mathematical strategies have few relevant applications, and these strategies might feel less personally meaningful for students than those applied to understand socio-scientific issues. Our research shows that socio-scientific issues may pose additional barriers to learning, but these barriers might be overcome with prompts to reflect, justify, and consider belief-inconsistent information among individuals who are open to such prompts.

We should also note, however, that when the outcome was plausibility perceptions or estimation skill, we found no consistent moderating effects. Compared with the stable indicators of emotion, motivation, and epistemic dispositions, future research might explore whether context-sensitive, state-based motivational emotional outcomes play a role in knowledge and plausibility revision (e.g., surprise), and explore causal relationships therein.

Limitations

The findings of this study are necessarily limited by several factors. First, while the pretest-posttest comparison group design that we employ is internally valid (see, e.g., Campbell & Stanley, 1963; Shadish et al., 2002), the external validity may be questionable. The main analytical sample identified as mostly White, female, had a higher median age than the general population of undergraduate students, and engaged with information in a controlled survey environment, limiting generalization to other contexts. Future research might modify and scale-up the central interventions for use in settings that are less controlled, more realistic, and with a more diverse population of learners that are better representative of undergraduate populations in the USA. Third, as noted, the limited conclusions drawn from the estimation skill measures should be taken with caution. As with prior attempts to capture measurement estimation skills (e.g., Hogan & Brezinski, 2003), the scales we created were not reliable at conventional levels (McDonald's omega < .60) and had inconsistent threshold values for partial credit scores. Future research might investigate the potential multidimensionality of measurement estimation and refrain from using potentially unreliable scales as the basis for conclusions. Fourth, there are certain contexts in which the validity of self-report measures are called into question (Stone et al., 2000). Particularly when individuals are asked to report their stance on topics that reflect their skills, abilities, or other sensitive topics, individuals tend to give responses that are socially desirable (e.g., Fowler, 1995; Fowler et al., 1998; Stone et al., 2000); as such, it could be the case that items from the plausibility perceptions measures led individuals to report in socially desirable ways. Fifth, we did not gather evidence of whether epistemic aims were influenced by the epistemic cognition prompts. Future research might seek to design measures that are sensitive to whether people have epistemic aims compared with non-epistemic aims. Sixth, our knowledge measure captured individuals' knowledge of scientific consensus around climate change issues but was unable to identify individuals who might have agreed that there is a consensus among scientists but distrust their conclusions. Future studies might consider including measures that are more sensitive to such distrust.

Support for the Plausibility for Conceptual Change Model and Two-Step Model

As predicted by the Plausibility Judgments for Conceptual Change model (Lombardi, Nussbaum, et al., 2016), findings from this study indicate that epistemic dispositions and numerical estimation skills may play a role in supporting conceptual change. Results support the idea that active open-minded thinking comprises an important factor that moderates knowledge revision processes, particularly for those presented with both estimation instruction and epistemic prompts (c.f. Sinatra et al., 2003). These findings provide support for Lombardi, Nussbaum, et al.'s (2016) Plausibility Judgments for Conceptual Change model, showing that, indeed, actively open-minded dispositions are important for supporting individuals' explicit assessments of numerical information and potentially for revising their conceptions as a result.

These findings are also consistent with the Two-Step model of source validation (Richter & Maier, 2017). We found that scientific knowledge at posttest was higher among people with greater willingness to reason with novel evidence, especially for those prompted to carefully consider quantitative evidence and explicitly process novel evidence. These learners may have more explicitly considered knowledge-inconsistent evidence and this explicit processing may have been boosted by the data evaluation skills emphasized in the interventions, thus leading to greater knowledge revision and fewer misconceptions as a result.

Implications for Instruction

The interventions used in this study might be adapted for both mathematics and science classrooms. The current EPIC intervention had only a modest impact on undergraduate students' knowledge overall, but such an intervention might have greater impacts if integrated into regular coursework over a longer duration of time. Secondary or undergraduate students might be encouraged to use analytic strategies to estimate important numbers as they learn about various topics in science or apply mathematical strategies to estimate relevant quantities in mathematics. In this way, mathematics teachers might use the EPIC approach to encourage their students to apply mathematical reasoning skills to understand the world, and science teachers might use this approach to encourage their students to engage with key scientific quantities related to their instruction—offering interdisciplinary practices that bridge mathematical and scientific reasoning skills. Another key finding in this study is that active open-minded thinking is an important epistemic disposition that facilitates scientific learning from numerical data. As such, teachers and professors might consider emphasizing to students the importance of keeping an open mind and the importance of examining new types of evidence, even if that evidence goes against their beliefs (Stanovitch & West, 1997).

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 numbers and illuminate mechanisms that underlie such shifts. By creating and testing instructional interventions, this study also explores a collection of strategies for better preparing people with these skills needed to navigate the minefield of deceptive data found in today's online news landscape.

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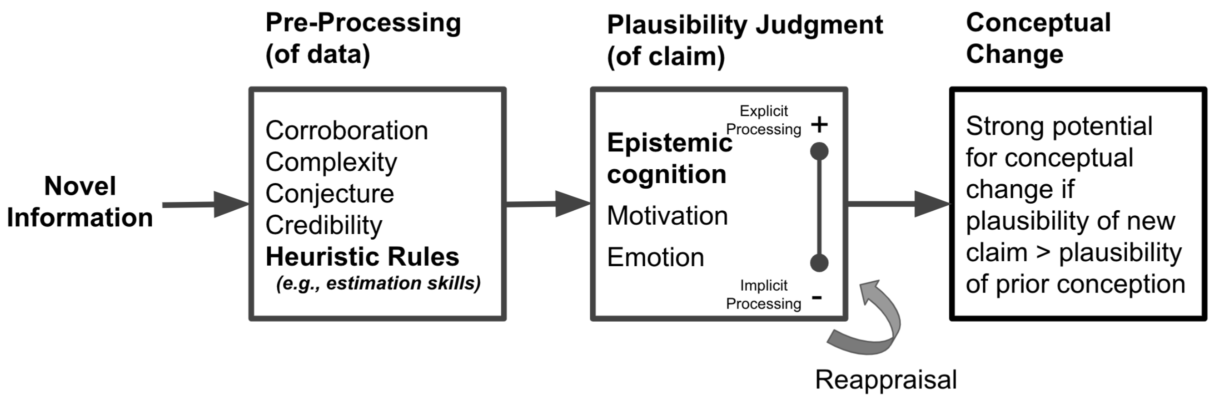
Figure 1

The Plausibility Judgments for Conceptual Change Model.



Note. Image adapted from Lombardi, Nussbaum, et al., (2016). Heuristic rules and Epistemic cognition are represented in bold because they are key factors that are manipulated in this study.

Figure 2

Visual Representation of the Survey Flow, Materials, and Procedures.

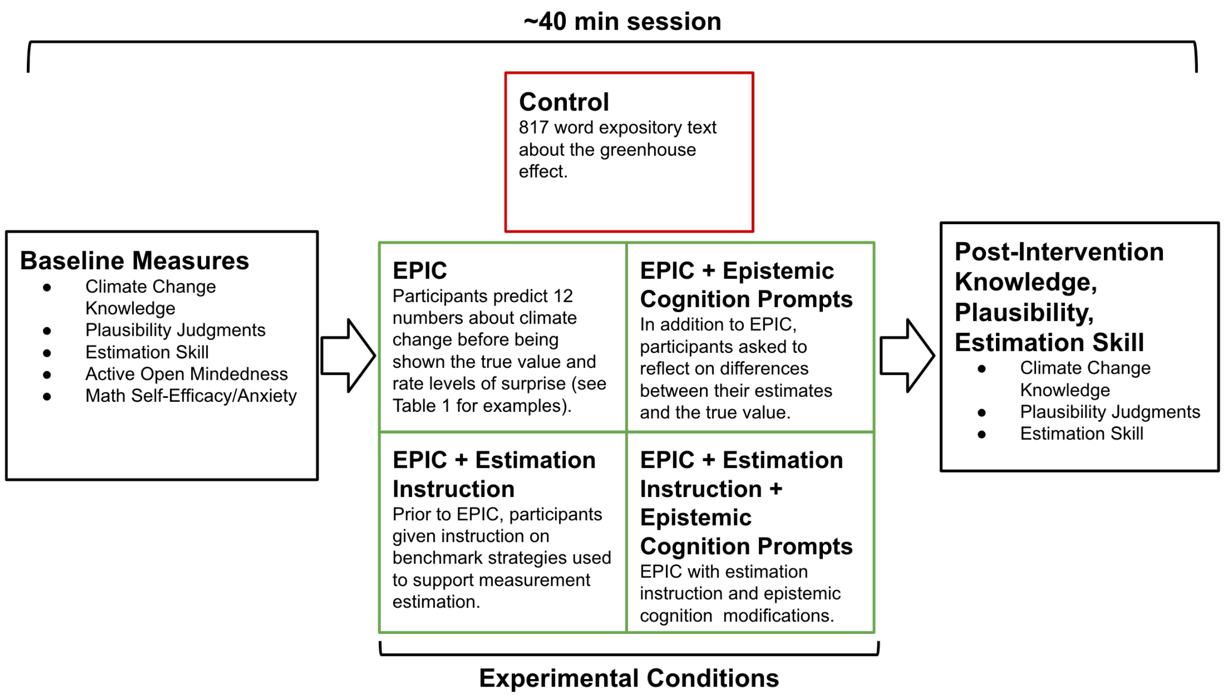
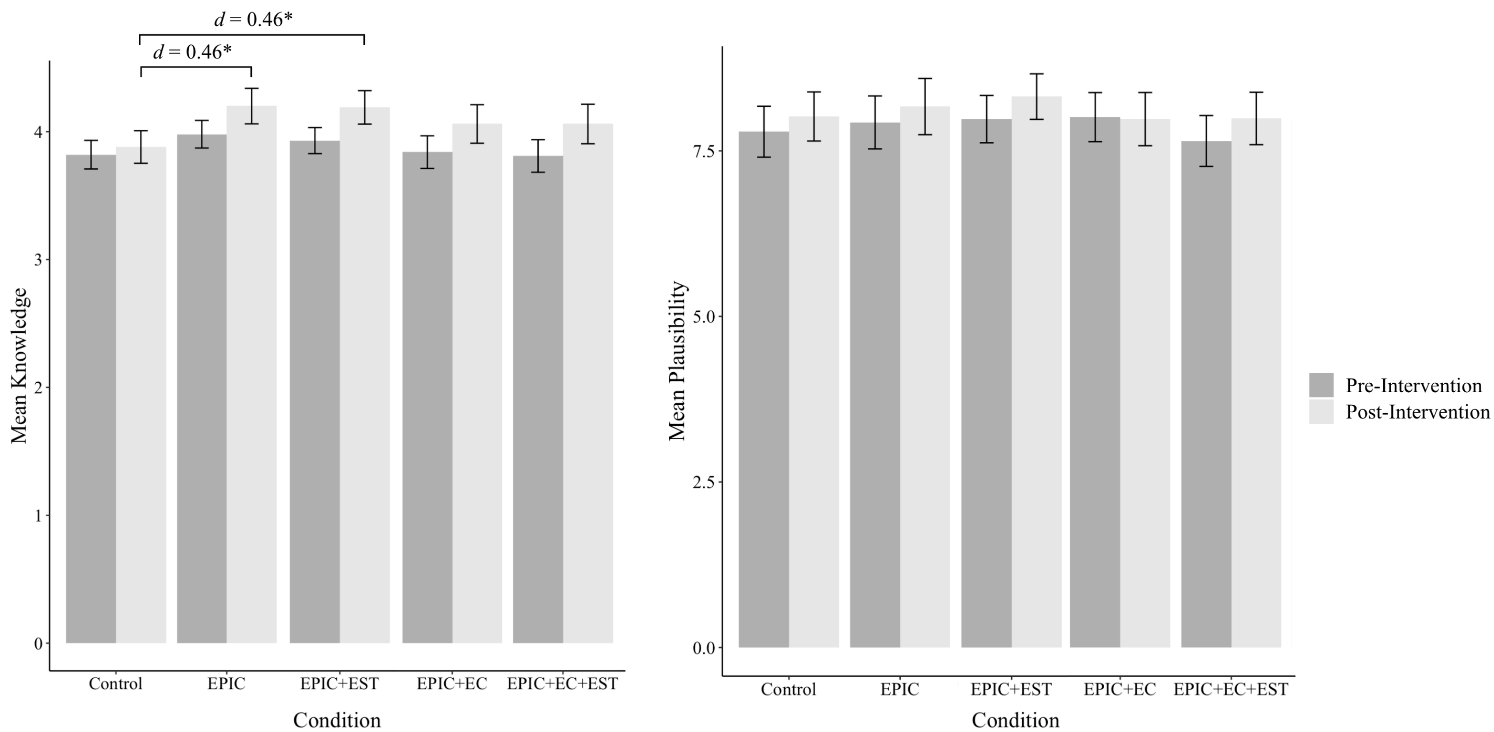


Figure 3

Mean Climate Change Knowledge and Plausibility Perceptions by Experimental Condition.



Note. Control = comparison condition in which participants read an expository text. EPIC = central intervention in which participants estimated climate change quantities before integrating the scientifically accepted estimate. EPIC + EST represents the intervention supplemented with estimation instruction. EPIC + EC represents the intervention supplemented with prompts to activate epistemic cognition. EPIC + EC + EST represents the intervention with both epistemic cognition and estimation skills modifications. Significance (* $p < .05$) has been Benjamini-Hochberg-adjusted for post-test subgroup comparisons. Error bars represent standard errors.

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
Researcher created	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.

Table 2

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

	Min, Max	*α*	Full Sample (*n* = 516)		Comparison Group (*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	.68	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	.83	4.08	0.74	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	0.21	0.73	0.26	0.49	0.25	0.65
Plausibility perceptions (pre)	1, 10	.95	7.87	1.97	7.79	1.99	7.93	2.07	8.01	1.92	7.98	1.86	7.65	1.99
Plausibility perceptions (post)	1, 10	.95	8.10	2.01	8.02	1.92	8.17	2.20	7.98	2.08	8.32	1.79	7.99	2.05
Estimation Skill (pre)	0, 3	.44	0.90	0.45	0.90	0.44	0.84	0.41	0.90	0.46	0.93	0.48	0.91	0.47
Estimation Skill (post)	0, 3	.54	1.03	0.41	1.11	0.39	1.02	0.38	0.97	0.44	1.05	0.36	1.01	0.45
Active open mindedness (AOT)	1, 5	.70	4.84	0.86	4.74	0.81	5.01	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

Note. EPIC represents the treatment conditions in which participants estimated numbers about climate change before being shown the true value. EST and EC are modifications to this intervention. EST signifies conditions that employed the estimation instruction modification. EC represents conditions that employed prompts to activate epistemic cognition.

Table 3

Intercorrelations Among Variables.

	1	2	3	4	5	6	7	8
1. Knowledge (pre)								
2. Knowledge (post)	.65***							
3. Plausibility (pre)	.65***	.60***						
4. Plausibility (post)	.55***	.68***	.76***					
5. Estimation skill (pre)	.08	.17***	.13**	.14**				
6. Estimation skill (post)	.12**	.27***	.18***	.28***	.32***			
7. Active Open-minded Thinking (AOT)	.41***	.51***	.43***	.48***	.22***	.26***		
8. Math self-efficacy	.16***	.14**	.15***	.16***	.09*	.08	.08	
9. Math anxiety	-.01	-.03	-.05	-.05	.01	.02	-.02	.63***

Note. * $p < .05$. ** $p < .01$. *** $p < .001$

Table 4

A Summary of Planned Contrasts For ANCOVA Analyses Testing Hypotheses 1–4.

		Contrast Coefficients					Knowledge as Outcome			Plausibility as Outcome		
Hypothesis Tested	Summary	EPIC (n=103)	EPIC+ EC (n=103)	EPIC+EST (n=104)	EPIC+ EC+EST (n=103)	Comparison Group (n=103)	*t*	*p*	*r*	*t*	*p*	*r*
H1	EPIC conditions vs comparison group	1	1	1	1	-4	**6.25**	**.002**	**.135**	0.09	.932	.003
H2	Estimation Instruction vs No Estimation Instruction	-1	-1	1	1	0	0.50	.614	.022	1.61	.109	.071
H3	Epistemic Cognition Prompts vs No Epistemic Cognition Prompts	-1	1	-1	1	0	0.57	.565	.025	-1.26	.209	.056
H4	Interaction Between Estimation Instruction and Epistemic Cognition Prompts	1	-1	-1	1	0	-0.01	.996	.000	0.62	.535	.027

Note. Results present coefficients from two ANCOVA models, one with posttest knowledge as the main outcome and pretest knowledge as the covariate, and one with posttest plausibility perceptions as the outcome and pretest plausibility as the covariate. EST and EC are modifications to this intervention. EST signifies conditions that employed the estimation instruction modification. EC represents conditions that employed prompts to activate epistemic cognition. Bold values represent effects that are significant at the $\alpha < .0125$ level, which uses an unordered Bonferroni correction to account for the four tests (Rosenthal & Rubin, 1984). Effect size was calculated using $r = t^2 / (t^2 + df)$ (Howell, 2009).

Table 5

Effects of Experimental Conditions on Post-Test Knowledge and The Moderating Effects of Math Efficacy, Math Anxiety, and Active Open-Minded Thinking.

	Climate Change Knowledge at Posttest: β (SE) *p*							
	No Moderator		Math Self-Efficacy as Moderator		Math Anxiety as Moderator		Actively Open-Minded Thinking as Moderator	
Prior Knowledge		**0.647*** **		**0.637*** **		**0.646*** **		**0.527*** **
		(0.039)		**(0.040)**		**(0.040)**		**(0.042)**
		<.001		**<.001**		**<.001**		**<.001**
EPIC	**0.426** **	**0.259** **	**0.444*** **	**0.266** **	**0.424** **	**0.259** **	**0.267* **	**0.199* **
	(0.132)	**(0.089)**	**(0.131)**	**(0.090)**	**(0.133)**	**(0.090)**	**(0.118)**	**(0.089)**
	.002	**.004**	**.001**	**.004**	**.002**	**.005**	**.024**	**.026**
EPIC+EC	0.236	**0.216* **	0.241	**0.219* **	0.236	0.216	0.185	0.198
	(0.138)	**(0.109)**	(0.139)	**(0.112)**	(0.139)	(0.110)	(0.120)	(0.103)
	.089	**.048**	.085	**.050**	.089	.051	.124	.055
EPIC+EC+EST	0.241	**0.253* **	0.241	**0.251* **	0.243	**0.257* **	**0.234* **	**0.256** **
	(0.140)	**(0.101)**	(0.139)	**(0.102)**	(0.141)	**(0.102)**	**(0.114)**	**(0.092)**
	.085	**.013**	.084	**.015**	.085	**.013**	**.041**	**.006**
EPIC+EST	**0.412** **	**0.296*** **	**0.425*** **	**0.302*** **	**0.414** **	**0.297*** **	**0.362** **	**0.295*** **
	(0.127)	**(0.087)**	**(0.126)**	**(0.087)**	**(0.128)**	**(0.087)**	**(0.115)**	**(0.087)**
	.002	**.001**	**.001**	**.001**	**.002**	**.001**	**.002**	**.001**
Moderator			0.108	0.002	0.071	0.013	**0.456*** **	**0.205*** **
			(0.087)	(0.054)	(0.084)	(0.054)	**(0.069)**	**(0.060)**
			0.214	0.974	0.401	0.806	**<.001**	**0.001**
EPIC*Moderator			0.040	0.054	-0.140	-0.017	0.062	0.125
			(0.126)	(0.081)	(0.121)	(0.079)	(0.102)	(0.085)
			.750	.505	.251	.831	.547	.144
(EPIC+EC)*Moderator			-0.118	-0.041	-0.210	-0.070	0.098	0.140
			(0.135)	(0.117)	(0.146)	(0.122)	(0.116)	(0.104)
			.384	.731	.150	.566	.397	.179
(EPIC+EC+EST)*Moderator			0.152	0.116	-0.103	-0.078	**0.218* **	**0.222* **
			(0.123)	(0.091)	(0.128)	(0.091)	**(0.107)**	**(0.089)**
			.215	.204	.422	.392	**.042**	**.013**
(EPIC+EST)*Moderator			0.125	0.092	-0.021	-0.015	-0.113	-0.052
			(0.12)	(0.083)	(0.115)	(0.080)	(0.113)	(0.091)
			.296	.271	.857	.849	.319	.567
Intercept	-0.263**	-0.205***	-0.268**	-0.206***	-0.264**	-0.205***	-0.210**	-0.192***
	(0.089)	(0.056)	(0.090)	(0.057)	(0.090)	(0.056)	(0.078)	(0.056)
	.004	<.001	.004	<.001	.004	<.001	.008	.001

Note. ~p < 0.1; *p < 0.05; **p < 0.01; ***p < .001. All moderators and knowledge variables were standardized around the mean prior to analyses. Boldfaced values indicate statistically significant results for predictors.

Table 6
Effects of Experimental Conditions on Post-Test Plausibility and The Moderating Effects of Math Efficacy, Math Anxiety, and Active Open-Minded Thinking.

Plausibility at Posttest: β (SE) *p*								
	No Moderator		Math Self-Efficacy as Moderator		Math Anxiety as Moderator		Actively Open-Minded Thinking as Moderator	
Prior Plausibility		**0.765*****		**0.761*****		**0.763*****		**0.686*****
		(0.040)		**(0.041)**		**(0.041)**		**(0.051)**
		<.001		**<.001**		**<.001**		**<.001**
EPIC	0.072	0.015	0.094	0.017	0.072	0.015	-0.070	-0.015
	(0.144)	(0.082)	(0.142)	(0.082)	(0.145)	(0.083)	(0.127)	(0.074)
	.618	.859	.510	.833	.618	.852	.584	.837
EPIC+EC	-0.020	-0.105	-0.021	-0.112	-0.019	-0.105	-0.073	-0.113
	(0.139)	(0.087)	(0.142)	(0.090)	(0.140)	(0.089)	(0.119)	(0.082)
	.887	.229	.880	.214	.890	.239	.537	.170
EPIC+EC+EST	-0.017	0.037	-0.015	0.035	-0.013	0.036	-0.033	0.029
	(0.138)	(0.077)	(0.137)	(0.077)	(0.139)	(0.078)	(0.114)	(0.072)
	.903	.632	.912	.653	.923	.645	.771	.684
EPIC+EST	0.151	0.077	0.161	0.076	0.148	0.075	0.098	0.069
	(0.129)	(0.090)	(0.129)	(0.089)	(0.130)	(0.089)	(0.111)	(0.085)
	.243	.391	.213	.393	.254	.400	.375	.421
Moderator			0.168	0.014	0.056	0.013	**0.483*****	**0.154***
			(0.086)	(0.038)	(0.082)	(0.048)	**(0.084)**	**(0.069)**
			.053	.715	.493	.788	**<.001**	**.026**
EPIC*Moderator			<0.001	0.005	-0.048	0.007	-0.065	-0.066
			(0.131)	(0.074)	(0.127)	(0.083)	(0.158)	(0.127)
			.999	.950	.703	.937	.681	.601
(EPIC+EC)*Moderator			-0.048	0.104	-0.209	-0.043	0.052	0.120
			(0.142)	(0.099)	(0.140)	(0.120)	(0.124)	(0.102)
			.738	.296	.137	.721	.675	.240
(EPIC+EC+EST)*Moderator			0.104	**0.128***	-0.113	0.004	0.102	0.079
			(0.117)	**(0.058)**	(0.119)	(0.071)	(0.114)	(0.078)
			.373	**.027**	.344	.953	.372	.308
(EPIC+EST)*Moderator			-0.089	-0.075	-0.159	-0.083	-0.064	0.036
			(0.125)	(0.108)	(0.113)	(0.103)	(0.121)	(0.107)
			.479	.491	.160	.423	.600	.739
Intercept	-0.037	-0.005	-0.044	-0.006	-0.038	-0.005	0.019	0.010
	(0.095)	(0.051)	(0.095)	(0.052)	(0.095)	(0.052)	(0.079)	(0.048)
	.693	.923	.642	.913	.693	.922	.806	.838

Note. $*p < 0.05$; $**p < 0.01$; $***p < .001$. All moderators and plausibility variables were standardized around the mean prior to analyses. Boldfaced values indicate statistically significant results for predictors.