

Supporting Secondary Students' Climate Change Learning and Motivation Using Novel Data and Data Visualizations

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Abstract.

National science standards at the secondary level currently recommend that students make sense of data constituting evidence of human-induced climate change; yet, secondary students continue to hold serious misconceptions about the topic. Thus, there is a need to create learning contexts that support climate change understanding, motivation, and data literacy for secondary students. The purpose of this preregistered study was to test an online intervention that presents novel climate change data and uses number-line data visualizations to support climate-change learning and motivation for secondary students. To this end, I conducted an experimental online study with 248 secondary students randomly assigned to either engage with the intervention, the intervention supplemented with number-line visualization feedback, or a control group. Findings revealed that the game conditions improved climate change knowledge and situated interest compared with the control, and knowledge effects were stronger among learners who expressed more openness to reason with belief-discrepant evidence. There were no significant effects of supplementing the game with number line feedback. Exploratory path analyses revealed that there were also indirect effects of the intervention on climate change learning, plausibility, and climate efficacy through epistemic emotions and motivation. Namely, the intervention was linked to these outcomes by decreasing boredom which predicted utility value and science interest. The study contributes to conversations around the role of data-literacy in supporting motivation for science learning and showcases an intervention that can be easily shared online.

Keywords: conceptual change, climate change, learning technology, STEM education

Highlights

- Tested the impact of an estimation game on secondary student learning and motivation.
- Found improved climate change knowledge and situated interest compared with a control.
- Effects were moderated by actively open-minded thinking and individual science interest.
- Explored indirect effects of the game through emotion and motivational processes.
- Supports the idea that data engagement can support learning, motivation, and action.

Supporting Secondary Students' Climate Change Learning and Motivation Using Novel Data and Data Visualizations

There is currently a need to promote climate change education at the secondary level. Despite increasing concern about climate change among young people across the globe (Hickman et al., 2021; Wray, 2022), climate change is under-emphasized in secondary education. Although the Next Generation Science Standards recommend that climate change be taught in U.S. schools beginning in fifth grade and incorporated into all science classes (NGSS, 2013), these standards are voluntary, and so far, only 20 states and the District of Columbia have adopted them. An expert review of the remaining 30 states revealed that 20 of them earned a C+ or lower because their standards did not require students to learn the scientific consensus on climate change: that it is real, severe, caused by humans, but that there is hope for change (NCES & TFNEF, 2020). Outside of the USA, the situation is not much better; only 45% of national education documents or curricula across 80 countries mention climate change at all (UNESCO, 2021).

There are many explanations for the slow improvements to climate change education (Cho, 2023), though a notable challenge is that climate change is a difficult topic to learn and high-quality learning activities are sparse. Climate change is tricky for secondary students to learn because, not only is it psychologically difficult to accept and address the looming threat of climate change (Stoknes, 2014), but evidence of climate change relies heavily on quantitative data and data representations, which secondary students tend to struggle with (Allen, 2018; Doyle, 2015; Harold et al., 2016; Vamvakoussi & Vosniadou, 2004; 2007; 2010). Partly due to these psychological and conceptual challenges, secondary students sometimes hold persistent misconceptions about human induced climate change, including about its main mechanisms,

severity of impacts, and question whether there's a scientific consensus on the matter (Dawson & Carson, 2013; McNeil & Vaughn, 2012). As such, there is a need to create engaging learning contexts that support climate change understanding and provide opportunities for students to make meaning of scientific data.

Fortunately, there are several approaches that support climate change learning, such as micro-interventions that present people with surprising numbers about climate change after they estimate those numbers (Ranney & Clark, 2016; Thacker, 2023; Thacker & Sinatra, 2022; Thacker et al., 2024a). Indeed, empirical research suggests that estimation interventions of this sort can reduce misconceptions and improve climate change acceptance, and that emotion, motivation, and beliefs about knowledge play important roles in such learning processes (Ranney & Clark 2016; Thacker, 2023; Thacker & Sinatra, 2022). Yet despite the effectiveness of this approach, few studies have tested its efficacy with secondary students or investigated whether the use of data visualizations may enhance this learning experience. Prior research has also investigated only a limited range of possible motivational and emotional mechanisms (i.e., mathematics anxiety and mathematics self-efficacy), and analyses exploring their indirect effects have not been studied. Furthermore, very few studies have explored whether such improved knowledge outcomes are related to learners' willingness to take *action* on climate change (also referred to as "climate efficacy;" Geiger et al., 2023). Following, I synthesize theory from educational psychology, STEM education, and climate change psychology to frame an experimental study in which I tested whether two variants of an intervention (one that presents quantitative feedback using a number line visualization and one that does not) would shift secondary students' climate change misconceptions when compared with a control group. Furthermore, I explored the role of a wider range of emotions and motivational factors in such

conceptual change processes and their relationships with climate efficacy.

Theoretical Framework

To frame how and why climate change data might shift scientific conceptions and climate efficacy, and how data visualizations might support this change, I integrate research on conceptual change (Dole & Sinatra, 1998; Lombardi et al., 2016a), numerical development (Siegler, 2016), and climate change psychology (Stoknes, 2015).

How Novel Data Can Support Conceptual Change

Conceptual change can be defined as a restructuring of knowledge to become more aligned with the scientific consensus (Dole & Sinatra, 1998). Several theories posit that novel information¹ can be the catalyst for such shifts in misconceptions (Dole & Sinatra, 1998; Lombardi et al., 2016a; Posner et al., 1982). For example, the Plausibility Judgments for Conceptual Change model (PJCC; Lombardi et al., 2016a) posits that when people are presented with novel information (such as surprising climate change data), they initially process the information, judge the plausibility of claims supported by the information, and then potentially restructure their knowledge and change their misconceptions as a result.

Several factors shape how learners initially process novel information. People can accurately interpret information only if it is *comprehensible* at their reading and quantitative reasoning levels, *coherent* with their prior experiences, *compelling* and relevant, and perceived as *valid* (e.g., data stems from a credible source and quantities seem reasonable) for conceptual change to occur (Dole & Sinatra, 1998). An important implication is that instructional designs

¹ In this study, I use the term “novel information,” to refer to evidence and “novel data” or “novel number” to refer to quantitative evidence (such as a number or a statistic) that is new or unfamiliar to learners and support a scientific concept, claim, or explanation (Lombardi et al., 2016). For example, the percentage of climate scientists who agree that it is very likely that humans are responsible for climate change (97%), would be considered a novel climate change number because it is a number that supports the claim that there is a scientific consensus on climate change.

might be considered more effective when they present novel, comprehensible, and compelling information in a way that might easily be perceived as personally relevant, valid, and credible.

After people initially process novel information, they judge the plausibility of the claims associated with it. Plausibility can be defined as a perception of potential truth of a claim, and such perceptions can be either implicit and unconscious or explicit and intentional. More explicit and thoughtful plausibility appraisals depend on the individuals' level of (a) motivation, (b) epistemic dispositions (i.e., beliefs about knowledge and processes of knowing), and (c) topic emotions (Lombardi et al., 2016a). For example, a learner faced with a new claim might consider the claim more carefully if they have higher levels of academic motivation in that they are engaged, interested, and view the claim as useful or important. People may also take new claims more seriously if they are open to consider new viewpoints and ideas. Indeed, theory and evidence suggest that motivational factors such as a learners' *individual interest* in STEM (a stable disposition), their *situated interest* (a state-based construct triggered by the environment), and *utility value* (perceived utility of learned information) are important process mechanisms involved in the use of interventions that support learning, and conceptual change (Hidi & Renninger, 2006; Hulleman et al., 2010; Hulleman & Harackiewicz, 2021; Seyranian et al., 2023). *Epistemic dispositions*—people's relatively stable beliefs about knowledge and processes of knowing—are also thought to predict explicit engagement with new claims (Lombardi et al., 2016a; Richter & Maier, 2017). For example, adaptive epistemic dispositions (which can be defined as people's openness to reason with belief-discrepant evidence; Stanovich & West, 1997) are predictive of explicit reasoning, depth in the search for knowledge, and potential for conceptual change (Emlen-Metz et al., 2020; Thacker, 2023). *Epistemic emotions* (emotions related to learning, e.g., surprise and curiosity) are also hypothesized to direct learners' explicit

attention to plausibility appraisals, given that they have reciprocal relationships with motivation, affect, and cognition (Linnenbrink, 2007; Lombardi et al., 2016a) and have been found to mediate systems of motivational, affective, and learning processes (e.g., Jacobson et al., 2021; Muis, Chevrier, & Singh, 2018, Muis et al., 2018; Thacker et al., 2020). As such, the PJCC assumes that emotion, motivation, epistemic dispositions are mechanisms that partly determine whether plausibility judgments are explicit or implicit. More explicit plausibility judgments are then hypothesized to increase the likelihood of plausibility reappraisals and conceptual change.

Indeed, evidence demonstrates that there are strong relationships between processing of novel information, plausibility perceptions, and conceptual change regarding climate change knowledge revisions (e.g., Lombardi & Sinatra, 2012; Lombardi et al., 2013; Lombardi et al., 2016b; Thacker, 2023; Thacker & Sinatra, 2022), and that plausibility perceptions and conceptual changes partly depend on motivational factors, emotional factors, and epistemic dispositions (Lombardi et al., 2016b; Thacker, 2023; Thacker & Sinatra, 2022). For example, prompting undergraduate students to estimate a dozen climate change numbers before presenting them with the true value has been shown to reduce misconceptions by a third of a standard deviation compared with a control group (Thacker & Sinatra, 2022), an effect that was stronger among students who also received instruction to bolster their quantitative comprehension skills and adaptive epistemic dispositions. These effects were replicated when the intervention was modified to present data to undergraduates in a game-like setting that provided estimation accuracy feedback and explanations to contextualize the scientific values, in which case, a significant effect on plausibility perceptions was also found potentially due to those modifications (Thacker, 2023). Furthermore, across these studies, mathematics specific self-efficacy (Thacker & Sinatra, 2022) and mathematics anxiety (Thacker, 2023; Thacker & Sinatra,

2022) were found to moderate the effects of data literacy instruction on knowledge and plausibility perceptions. Evidence from qualitative interviews were also consistent with these findings and additionally identified specific mathematical skills that were crucial for data comprehension in the context of this estimation game (Thacker et al., 2024a).

However, despite this evidence demonstrating that novel data supports plausibility perceptions, conceptual change, and that there are synergistic effects of interventions that promote comprehension of that information, there are several gaps in the empirical literature. First, undergraduate students are largely overrepresented in the empirical literature, despite the need to study and improve climate change education for secondary students. Second, prior research has explored only emotional and motivational mechanisms that are trait-based and mathematics-specific (i.e., math self-efficacy and math anxiety). State-based emotions and motivational variables (such as interest, task value, and epistemic emotions) are important outcomes in themselves, and are also hypothesized to serve as mechanisms in learning processes (Huelleman et al., 2021) that likely play a role in conceptual change. Third, few research studies have investigated whether learning interventions that shift student conceptions also influence behaviors or intended behaviors. Even learners who have accurate scientific understandings and plausibility perceptions of climate change may not feel empowered to change their behavior. As I will describe in more detail in the next section, research in climate change psychology may help illuminate relations between climate change plausibility, conceptions, and intended action.

Strategies for Overcoming Psychological Barriers and Promoting Climate Efficacy

An important goal of this study was to assess whether a climate change learning intervention with hopeful messages might also shift students' climate action intentions. But before discussing strategies for promoting climate action, it may be helpful to first discuss

psychological barriers that learners must overcome to do so.

There are several psychological barriers preventing people from readily changing their climate change-related beliefs, knowledge, and behaviors. Information about climate science can be threatening and motivate some learners to resist engagement for a number of reasons. For example, Stoknes (2015) identified five major psychological barriers to individuals' thinking about, understanding, and acting on climate change called "the five Ds:" *distance*, *doom*, *dissonance*, *denial*, and *identity*. Drawing from evolutionary, cognitive, and social psychology, Stoknes argued that people avoid thinking about climate change in order to: (1) *distance* themselves from the topic and avoid responsibility to take action on climate change; (2) prevent a sense of *doom* associated with seemingly apocalyptic global problems; (3) reconcile the cognitive *dissonance* that emerges from realizing that their actions conflict with their moral beliefs; (4) uphold a sense of climate change *denial*; and (5) protect their *identity* from negative stigmas. Conceptual change can be inhibited by the 5Ds in that they interrupt the processing of information, as well as motivation and emotions that facilitate change. For example, climate change distancing and denial are considered to be central psychological mechanisms that lead people to resist change and stick to their existing conceptions rather than accepting that they might be wrong (Sinatra & Hofer, 2021). Doom is essentially a collection of negative deactivating emotions (e.g., hopelessness and anxiety) that people experience when considering the implications of climate change, which can interrupt emotions that are more productive for learning such as curiosity, surprise, and interest (e.g., Clayton, 2020; Pekrun, 2006). Identity threats have implications for motivation, in that people who are members of social groups that collectively identify with climate change skepticism or perceive it to have low personal relevance have low motivation to learn and change (Bliuc et al., 2007; Schulte et al., 2020).

Fortunately, there are strategies for upending these persistent barriers. For example, Stoknes (2015) makes several recommendations on how climate change messages can be crafted to promote deeper engagement with information and promote the potential for action. Information can be more engaging if the issue feels more *personal and urgent*; it is more difficult for learners to distance and deny information that has pressing implications for personally relevant topics. Stoknes also recommends promoting positive emotions, for example, by using *supportive framings* (rather than catastrophic framings) and by suggesting opportunities for *viable action*.

In this study, I aimed to leverage these message characteristics to help individuals overcome psychological barriers by promoting climate change hope. Climate change hope is often conceived as a multidimensional construct that involves, for example—*personal climate efficacy* (personal willingness to take action and perceptions that there are courses of action that will make a difference), *collective climate efficacy* (the belief that the society will be able to address climate challenges as a collective) and *lack of climate efficacy* or hopelessness (the belief that climate change is beyond the control of the individual or collective; e.g., Li & Monroe, 2018; Ojala, 2022).² In a metaanalysis of $k=46$ quantitative studies, Geiger et al., (2023) found that personal climate efficacy was strongly associated with climate change action and engagement ($r=.40$). Further, interventions that targeted hope had significant but small effects on climate engagement ($d=.08$) and effects were stronger among interventions that targeted personal efficacy ($k=2$, $d=.18$). Though this evidence represents early attempts to promote climate action/engagement, with stronger correlational evidence than causal evidence, it begins to

² These dimensions of climate change hope have alternative terms used to refer to them (e.g., “personal-sphere will and way,” “collective-sphere will and way,” and “lack of will and way”; e.g., Li & Monroe, 2018). In this paper, I use the terms personal climate efficacy, collective climate efficacy, and lack of climate efficacy to align with language used by Geiger et al., (2023) and for the sake of brevity.

indicate that promoting personal efficacy and collective agency can support behavioral outcomes.

The current study aimed to create and test an intervention that leveraged personal climate efficacy, specifically by presenting salient evidence indicating the *urgency* of climate change, *contextualizing* that evidence, emphasizing *action opportunities*, promoting *positive emotions and motivation*, and *avoiding blaming or shaming* participants in a game-like environment. Games, in particular, have the potential to emotionally engage learners, providing them with a sense of control and efficacy, and can be grounded in situated understandings of the world (Janakiraman et al., 2018; Gee, 2008). A key attribute of the game that I designed for this study was the incorporation of data visualizations using a linear number line.

Visualizations of Scientific Data: The Linear Number Line

In addition to promoting motivation, engagement, and active reflection on personal climate stances in a game-like learning environment, a central goal of this study was to promote a predictor of these outcomes: students' comprehension of novel climate change data. I aimed to support data comprehension with the use of number visualizations.

Research suggests that data visualizations can greatly support students in making personal meaning from scientific quantities and advance the development of their numerical knowledge. Siegler's (2016) Integrated Theory of Numerical Development posits that people develop an accurate understanding of number magnitudes and their relationships as they connect numbers (e.g., representing rising global temperatures) to the things that those numbers refer to (e.g., global climate change). Such connections between numbers and their referents are hypothesized to happen through processes of *analogy and association*, as facilitated by conventional numerical representations and visualizations.

A particularly useful visualization for representing climate change numbers is the linear number line (hereafter referred to as “the number line”), which depicts number magnitudes on a line using a linear scale. The number line is widely considered to be a central mathematical representation of real numbers and is particularly useful for comparing magnitudes and representing arithmetic operations, among many other uses (Van De Walle et al., 2013). Such representations have potential to help students ground abstract number concepts in sensory perceptions, enable quick comparisons and associations with well understood quantities, and can support both math and science learning, retention, interest, and active engagement (Gunderson et al., 2012; Schwartz & Heiser, 2006; Siegler, 2016; Saxe et al., 2013; Stevens & Hall, 1998). In particular, I decided to integrate number lines into a climate change intervention to help learners understand and compare differences between their estimates of climate-related numbers and scientifically accepted values.

Despite evidence across several studies finding that presenting students with raw climate change quantities can support their comprehension and learning (Ranney & Clark, 2016; Thacker, 2023; Thacker & Sinatra, 2022), to date, no research has attempted to enhance the learning that occurs from novel scientific data by integrating conventional number line representations into number estimation tasks. Additionally, of the few studies investigating estimation of real-world quantities with secondary students (e.g., Munich et al., 2007), none utilize experimental study designs, utilize visualizations, nor focus specifically on supporting climate change learning or climate efficacy. As such, a main purpose of this study was to support students’ data comprehension and reflection on potentially belief-discrepant data by providing them with number line visualizations that facilitate comparisons of their estimates with the actual values.

Summary of Theoretical Framework

In sum, theory suggests that novel data has the potential to shift people's thinking and climate efficacy (see Figure 1). When individuals are presented with novel data, they initially process the information which partly depends on their ability to comprehend the information (Dole & Sinatra 1998; Lombardi et al., 2016a; Siegler, 2016), then judge the plausibility of associated claims, which depends on their emotion, motivation, and epistemic dispositions (Lombardi et al., 2016a), which then predicts their potential for conceptual change (Dole & Sinatra, 1998). Climate efficacy may also be promoted if messages that learners encounter are relatable, emphasize action opportunities, yet maintain urgency (Stoknes, 2015). Of the factors involved in this process, the current study tested whether novel data would improve learning and motivational outcomes, whether data-visualizations would enhance these outcomes, and explored the extent that motivational and emotional processes might serve as mechanisms underlying these change processes.

[FIGURE 1 AROUND HERE]

Current Study

The current research explored several relationships depicted in this theoretical framework by testing an intervention that presented secondary students with novel data about climate change in a game-like environment. Specifically, this project investigated the effect of a novel design feature that may enhance comprehension of climate change data: number line visualizations. The intention was to support math and science learning by enabling mathematical comparisons between estimated climate change numbers with known quantities, encouraging integration of novel climate change numbers, and improving engagement. Another goal of the current study was to explore the extent that emotional and motivational factors might serve as

mechanisms underlying effects of the estimation game and their predictivity of climate efficacy.

As such, this study included a combination of pre-registered and exploratory analyses. Three related research questions and hypotheses were preregistered on the Open-Science Framework (<https://osf.io/tncx3>) and are addressed in this study, as well as one exploratory research question.

Preregistered Hypotheses

- *Hypothesis 1 (H1)*. I hypothesized that students assigned to the intervention conditions would have greater knowledge, situated interest, utility value, and find climate change to be more plausible at posttest when compared with those assigned to read an expository text.
- *Hypothesis 2 (H2)*. I hypothesized that supplementing the intervention with number line visualization feedback would support (H2.1) climate change knowledge, (H2.2) plausibility, and (H2.3) situated interest compared with those who were assigned to the intervention but without the visualization feedback. (H2.4) I expected no significant differences in utility value between these conditions.
- *Hypothesis 3 (H3)*. I hypothesized that effects would be stronger among people with higher levels of (H3.1) adaptive epistemic dispositions, (H3.2) number line knowledge, (H3.3) individual science interest, and (H3.4) weaker among people with math anxiety.

Exploratory Research Question

- *Exploratory Research Question*. To what extent will there be indirect effects of the intervention on climate change knowledge, plausibility, and efficacy through emotional and motivational processes?

Methods

Participants

To address these hypotheses, I recruited 248 secondary students from a Qualtrics panel of secondary students (grades 9–12) whose parents consented to allow their children to participate in an online science learning experiment.³ The intended sample size (245) was based on a rounded estimate from a power analysis using G*Power which found the sample size required to detect an effect size of .2 for an equal samples three-group analysis of covariance (ANCOVA) with power of .8 and alpha level of .05 (Faul et al., 2009); and furthermore, a sample of at least 224 is recommended to detect small indirect effects at .8 power (Fritz & Mackinnon, 2007).

To obtain this sample, Qualtrics representatives initially used multiple platforms to widely share a survey link online; 705 people initially clicked on the link to participate, but 110 were dropped from the analysis because they did not meet the eligibility criteria (student between grades 9 and 12), 155 were dropped because they did not agree to participate, 137 were dropped because they did not pass an attention check, 37 were dropped because they quit the study before completing the intervention, and 18 dropped because they were flagged as “speeders” by the algorithm created by Qualtrics. There was no missing data at pretest or posttest.

Participants’ age ranged from 14 to 18 years, with a mean of 16.4 years, and were in grades 9–12 (18% 9th, 23% 10th, 26% 11th, 18% 12th, 16% Other/Prefer not to say). Students identified as 23% Hispanic, 53% White, 21% Black, 10% Asian, 6% Two or more races, 2% American Indian/Alaska Native, 8% Other race, 56% female, 38% Male, 5% non-binary/other

³ According to Qualtrics documentation, standard recruitment and validation of the parent participant pools were as follows: “[Participating parents] were recruited from various sources, including website intercept recruitment, member referrals, targeted email lists, gaming sites, customer loyalty web portals, permission-based networks, and social media, etc. Consumer panel members’ names, addresses, and dates of birth are typically validated via third-party verification measures prior to their joining a panel. B2B participants are subject to additional quality control measures such as LinkedIn matching, phone calls to the participant’s place of business, and other third-party verification methods (TrueSample, RelevantID, Verity, etc.).” (Qualtrics, n.d., p.1).

gender.

Materials & Procedure

All participants engaged in a pretest, posttest, control group experimental design (see Figure 2). The pretest questionnaire measured students' misconceptions and plausibility perceptions of climate change (Lombardi et al., 2013), Actively Open Minded Thinking (AOT) to indicate adaptive epistemic dispositions (Stanovich & West, 1997), prior number line estimation skill (Siegler et al., 2011), and mathematics anxiety (Ganley et al., 2019).⁴ Then students were automatically directed to a web app that randomly assigned them to one of three conditions (a control group that read an expository text about the greenhouse effect, the estimation game intervention, or the modified estimation game supplemented with number line visualization feedback; see "Experimental Conditions" section for more detail). The posttest questionnaire measured climate change knowledge and plausibility, STEM interest (situated interest, individual science interest, and utility value; Hulleman et al., 2010), epistemic emotions (Pekrun et al., 2017), climate change hope (personal efficacy, collective efficacy, lack of efficacy; Li & Monroe, 2018), and a demographics questionnaire. Items within each scale were presented in a randomized order. All scales were piloted with 12 secondary students in cognitive interviews to ensure that measures were interpreted as intended. As a result of these pilots, the language was adapted to ease interpretation. Survey materials, intervention/control texts, data, and analysis scripts are available on the Open Science Framework (<https://osf.io/e4gcd/>).

[FIGURE 2 AROUND HERE]

Dependent Variables

⁴ The math anxiety and number line estimation skill scales were presented in a random order to avoid priming effects. That is, about half of the participants ($n=132$) completed the math anxiety questionnaire before the math questions, whereas the other half ($n=116$) completed math questions before the math anxiety questionnaire.

Climate Change Knowledge. Knowledge of climate change was measured using seven items adapted from the Human Induced Climate Change Knowledge measure (HICCK; Lombardi et al., 2013), as done in prior research (Thacker, 2023; Thacker & Sinatra, 2022). Participants shared the extent they believed that *climate scientists* would agree that certain statements are true (e.g., “The average sea level is increasing. This is evidence of climate change.”) on a seven-point agreement scale ranging from 1 (strongly disagree) to 5 (strongly agree). As such, agreement on this scale represents accurate conceptions about the scientific consensus around climate change, disagreement represents misconceptions, strength of agreement represents confidence in those stances, and “neither agree nor disagree” represents uncertainty. Participants completed this scale pre-intervention and post-intervention ($\alpha_{\text{pre}}=.59$, $\alpha_{\text{post}}=.76$). Construct and content validity of this scale was established through cognitive interviews with secondary students (Thacker et al, 2024b), and previously with undergraduate students (Lombardi et al., 2013; Thacker et al., 2024a).

Plausibility. Perceptions of plausibility that humans are responsible for climate change were measured using four items adapted from the Plausibility Perceptions Measure (PPM; Lombardi et al., 2012). These four items were used in prior research in a similar context (Thacker, 2023; Thacker & Sinatra, 2022). The items were intended to capture students’ *personal* perceptions of whether humans are responsible for climate change as they responded to statements (“Evidence from around the world shows that the climate is changing in many regions”) on a six-point agreement scale from 1=*Highly Implausible (or even impossible)* to 6=*Highly Plausible*. This scale was completed at pretest and posttest ($\alpha_{\text{pre}}=.77$, $\alpha_{\text{post}}=.83$).

STEM Interest. STEM interest was measured using a scale adapted from Hulleman et al., (2010) consisting of 10 total items comprising three scales (Situated Interest, individual

science interest, and Utility Value) prompting people to respond to statements on a seven-point agreement scale. The situated interest subscale consisted of three items capturing learners' context-dependent interest, specifically regarding the experimental condition they were assigned to (e.g., "I enjoyed this activity as a way to learn about climate change;" $\alpha=.84$). The individual science interest subscale was adapted from the STEM interest scale (Hulleman et al., 2010) and consisted of three items that captured a stable and long-term interest in science (e.g., "I've always wanted to learn more about science;" $\alpha=.77$). The utility value subscale was four items that measured learners' perceptions that the task relates to their future goals (e.g., "What I learned in this activity is relevant to my life;" $\alpha=.85$). Situated interest and utility value means were included as main outcomes in analyses, mean individual science interest was considered in exploratory analyses.

Climate Change Hope. At posttest, participants completed a Climate Change Hope Scale for High School Students (CCHS) adapted from Li & Monroe (2018), a scale that was selected in favor of traditional environmental efficacy scales (e.g., van Zomeren et al., 2010) because it was validated with high school students (rather than undergraduates) and captures three relevant subscales (rather than one) that contain similar items⁵ to traditional climate efficacy scales. The Climate Change Hope scale consisted of 11 items comprising three subscales in which participants rated their agreement to statements on a seven-point agreement scale. The first subscale consisted of three items capturing participants' individual climate efficacy and willingness to take action to mitigate climate change (e.g., "I am willing to take actions to help solve problems caused by climate change;" $\alpha=.71$). The second subscale consisted

⁵ To exemplify the similarity between the CCHS and traditional efficacy scales, I encourage the reader to compare the two items: "My individual actions will contribute to a solution of the climate crisis" (Zomeren et al., 2010) and "I know that there are things that I can do to help solve problems caused by climate change" (Li & Monroe, 2018).

of five items capturing participants' collective climate efficacy (e.g., "If everyone works together, we can solve problems caused by climate change;" $\alpha=.81$). The third subscale consisted of three items capturing climate hopelessness (e.g., "Climate change is beyond my control, so I won't even bother trying to solve problems caused by climate change;" $\alpha=.70$). Means were calculated for each subscale and used as outcomes in exploratory path analyses.

Covariates

Math Anxiety. Math anxiety was measured using a 9-item scale adapted from Ganley et al. (2019), prompting students to rate their agreement with statements such as "I get nervous when I think my math ability is being evaluated" ($\alpha=.93$).

Actively Open-Minded Thinking. The Actively Open-Minded Thinking scale (Stanovich & West, 1997) was used to measure adaptive epistemic dispositions and consisted of seven statements (e.g., "Changing your mind is a sign of weakness") that students rated on a seven-point agreement scale ($\alpha=.72$). The scale was originally validated with undergraduate students, but modified from its original form for this study after pilot interviews with secondary students using revised language that is more accessible for this group (Thacker et al., 2024b).

Number Line Estimation Skill. Number line estimation skill was measured using 12 items adapted from Siegler et al., (2011). Six items presented fractions (1/19, 8/11, 12/7, 19/8, 7/2, 13/3), six presented decimals (0.313, 1.701, 2.543, 3.210, 3.900, 4.250) and for each asked, "Where does this number go on the number line (0 to 5)?" with an unlabeled number-line as a response scale. Each item was recoded as either correct or incorrect: "correct" if their estimate was within ± 0.5 of the true value, "incorrect" if not. A sum score composite was used in all analyses ($\alpha=.64$).

Epistemic Emotions. Emotions were measured using the Epistemically Related

Emotions Scale short form (Pekrun et al., 2017), which prompted participants to report the intensity of seven emotions (surprised, curious, excited, confused, anxious, frustrated, bored) that they experienced while learning. Positive and negative emotion subscales were not reliable at conventional levels, so I used individual emotion items in exploratory path analyses.

Interventions and Experimental Conditions

Between pretest and posttest, participants were randomly assigned to one of three conditions within the web app environment: a control group, an estimation game group, and a group that received the estimation game modified with number-line visualization feedback. (See Appendix A for examples, see Supplemental Materials, Appendix SJ and SK for the full materials.)

Control Condition. The control group presented participants with an 817-word expository text about human contributions to the greenhouse effect adapted from Lombardi et al., (2013). This text was chosen to account for the time students would have spent engaging in the estimation game by reading a text about climate change that might be equally or more engaging than what is found in typical high school science textbooks. In addition to describing how the greenhouse effect works, the control text discussed several topics that were also covered in the intervention conditions. Both noted that greenhouse gasses (such as carbon dioxide and methane) are responsible for trapping heat in the atmosphere, that humans are responsible for adding greenhouse gasses to the atmosphere, which causes temperatures to rise and global ice cover to melt, and that about 97% of climate scientists agree that climate change is happening. The reading level of the control text (Flesch reading ease level: grades 10–12) was slightly easier than climate change sections found in traditional high school textbooks (Flesch reading ease level: grades 10.7–14.7; Eichhorst et al., 2020). Unlike many traditional textbook chapters on

climate change published since 2010, the control text also included a call to action (“If global warming is not mitigated, we run the risk of Earth’s temperature rising to unsafe levels”; Ansari & Landin, 2022).

Estimation Game. The estimation game condition prompted learners to estimate 12 climate change quantities before being presented with the scientifically accepted answer. Half of these estimation prompts included “hints,” or given values that might be used to estimate the unknown values better. Each scientifically accepted number appeared in a pop-up window along with accuracy feedback in the form of one to five “gold stars,” a short explanation to contextualize the true value, a related opportunity/suggestion for climate action, and links to the sources of the information to improve credibility.

Estimation Game + Visualization Feedback. The modified game condition was identical to the baseline estimation game, but modified with additional number line visualization feedback. Namely, this version of the game supplemented the feedback information (gold stars, explanations, calls to action, and sources of information) with a number line visualization displaying the students’ estimate in comparison with the scientifically accepted value.

Analytic Approach

To assess the effects of the interventions on the knowledge, plausibility, situated interest, and utility value outcome variables (H1–H2), I used OLS regression with robust standard errors using a separate model for each outcome. The main predictor was the treatment condition and covariates were pre-test scores whenever applicable. Given that the treatment predictor had three levels, hypotheses H1 and H2 were tested using two sets of contrasts: the first compared the control to an average of the two treatment conditions, the second compared the two variants of the Estimation Game (Estimation Game vs Estimation Game + Visualization Feedback). To

investigate moderating factors (H3), in separate models, I also included epistemic dispositions, number line estimation skill, and math anxiety as moderators of intervention effects. Lastly, I explored whether the treatment would indirectly affect knowledge, plausibility, or climate efficacy outcomes through emotional and motivational variables using path model analyses. Preregistered questions, hypotheses, and analyses were submitted to the Open Science Framework prior to data collection (<https://osf.io/tncx3>).

Results

Preliminary Analyses

Prior to running the main analyses, I first tested model assumptions and confirmed that pretest variables did not significantly differ by condition. Preliminary analyses revealed no significant preexisting differences between conditions for all main outcomes and predictors. Namely, there were no significant between-condition differences in pretest knowledge ($F=0.02$, $p=.982$), pretest plausibility perceptions ($F=1.62$, $p=.201$), epistemic dispositions ($F=0.48$, $p=.621$), mathematics anxiety ($F=2.01$, $p=.136$), age ($F=0.978$, $p=.377$), number line estimation accuracy ($F=0.04$, $p=.959$), gender ($\chi^2=8.43$, $p=.208$), or race ($\chi^2=10.12$, $p=.430$). Skew ranged from -1.12 to $.48$ and kurtosis from -1.15 to 0.98 for all continuous variables, which is considered acceptable (Tabachnick & Fidell, 2013). Further, Levene's tests revealed that variances were not statistically different between experimental groups across all analytic variables (all $ps > .117$). Descriptive statistics by condition and intercorrelations among all main outcomes and covariates are presented in Table 1.

[INSERT TABLE 1 AROUND HERE]

However, despite relatively balanced scores across pretest variables, one unexpected imbalance was among the number of individuals assigned to each condition ($n_{\text{control}}=64$,

$n_{\text{game}}=53$, $n_{\text{game+numberline}}=131$). Surprisingly, substantially more people who were assigned to the control and baseline intervention condition did not meet the inclusion criteria for the study, revealing imbalanced groups. To infer power losses from imbalanced groups, I conducted a Monte Carlo simulation using the SimDesign package in R (Chalmers & Adkins, 2020) and compared power of a relatively balanced three-sample ANCOVA with sample size 248, alpha .05 and effect size of $f = .2$ to the same model but with the unbalanced group proportions found in this study. After 100,000 simulations, results revealed that power decreased from .808 to .747.

As with the prior research (Thacker, 2023; Thacker & Sinatra, 2022), I found significant improvements in knowledge ($d=0.32$, $p<.001$) and plausibility perceptions ($d=0.12$, $p=.001$) from pretest to posttest on average. Further, I confirmed that there was no significant interaction between conditions and pretest knowledge ($p=.979$), or pretest plausibility ($p=.306$) suggesting that the data met assumptions for the planned analyses (Murnane & Willett, 2010).

Preregistered Analyses

Intervention effects on Knowledge, Plausibility, Situated Interest, and Utility Value (H1).

Multiple regression analyses revealed that students assigned to the estimation game conditions had significantly higher levels of climate change knowledge ($d=.23$, $p=.020$) and situated interest ($d=.30$, $p=.030$) than the control group at posttest, as predicted. However, contrary to hypotheses, there were no significant main effects of the interventions on plausibility perceptions or utility value (all $p>.385$).

Number-Line Effects on Knowledge, Plausibility, Situated Interest, and Utility Value (H2).

Contrasts comparing between the two versions of the estimation game revealed no significant effects of the visualization feedback on knowledge, plausibility, or utility value (all $p>.263$), contrary to my hypotheses.

Moderating Effects of Math Anxiety, Actively Open-Minded Thinking, Individual Science Interest, and Number Line Estimation Skill (H3).

The results of the moderation analyses are presented in Table 2, which depict the combined effect of the game conditions compared with the control as well as main effects and moderating effects of math anxiety, adaptive epistemic dispositions, individual science interest, and number line estimation skill (for results comparing each game variant to the control, see Table S1 in the Supplemental Materials).

[INSERT TABLE 2 AROUND HERE]

Several factors moderated the effects of the intervention. When the outcome was posttest knowledge, I found that epistemic dispositions ($\beta=.216, p=.044$) significantly moderated the effects of the interventions after controlling for pretest knowledge. That is, learners who were open to reason with belief-discrepant evidence gained more from the estimation game.

When the outcome was posttest climate change plausibility, I found a negative main effect of math anxiety ($\beta= -.092, p=.017$) but a positive moderating effect of the intervention conditions ($\beta=.110, p=.045$) after adjusting for pretest plausibility. In other words, the negative relationship between math anxiety and climate plausibility was negligible in the intervention conditions.

When the main outcome was situated interest, I found a significant moderating effect of number line estimation skill ($\beta=.331, p=.017$). That is, people with higher baseline number line estimation skill received a larger situated interest boost compared with the control.

When utility value was the outcome, I found a significant and positive main effect of individual science interest ($\beta=.258, p=.009$), and a positive moderating effect of individual science interest ($\beta=.276, p=.006$). In other words, learners with higher levels of individual

science interest also tended to view climate science as useful for their lives, particularly among students in the intervention conditions.

Exploratory Analysis

To explore the extent that epistemic emotions indirectly affect relations between the intervention and main outcomes, I ran a path model testing a logic model that synthesizes relationships hypothesized by theories of conceptual change (Dole & Sinatra, 1998; Lombardi et al., 2016), theory on the use of interventions that promote utility value (Hulleman & Harackiewicz, 2021), and climate change psychology (Stoknes, 2014). Specifically, I tested the hypothesized model shown in Figure 3, which depicts the combined effect of the estimation game variants (compared to control) predicting epistemic emotions (surprise, confusion, curiosity, boredom, anxiety, frustration, and excitement), followed by motivational variables (utility value, personal and situated science interest), followed by conceptual change outcomes (climate change knowledge, plausibility perceptions, personal climate efficacy, collective climate efficacy, and hopelessness).

[INSERT FIGURE 3 AROUND HERE]

To explore these relations, I used maximum likelihood estimation with robust Huber-White standard errors and a scaled Yuan-Bentler test statistic. I allowed for all variables within each of the emotion, motivation, and outcome stages to correlate and included pre-intervention variables to covary with their post-intervention counterparts (i.e., for knowledge and plausibility variables). All continuous variables were standardized around the mean prior to analyses. All analyses were conducted using the “lavaan” 0.6-3 package (Rosseel, 2012) in R.

Findings

Figure 4 shows the full path model with all coefficients. The initial model had

satisfactory fit ($\chi^2=82$, $df=34$, $CFI=.97$, $AIC=9658$, $RMSEA=.076$; Hu & Bentler, 1999).

[INSERT FIGURE 4 AROUND HERE]

The intervention influenced epistemic emotions. As depicted in Figure 4, there was a significant effect of the intervention conditions on reported surprise ($\beta=.45$, $SE=.17$, $p=.007$) and boredom ($\beta=-.68$, $SE=.15$, $p<.001$) with no significant effects on confusion, curiosity, frustration, anxiety, or excitement.

Epistemic emotions predicted motivational variables. Namely, curiosity was significantly and positively associated with situated interest ($\beta=.31$, $SE=.06$, $p<.001$), individual science interest ($\beta=.225$, $SE=.04$, $p<.001$), and utility value ($\beta=.36$, $SE=.06$, $p<.001$). Boredom significantly and negatively predicted situated interest ($\beta=-.27$, $SE=.04$, $p<.001$), individual science interest ($\beta=-.18$, $SE=.05$, $p<.001$), and utility value ($\beta=-.18$, $SE=.05$, $p<.001$).

Motivation then predicted knowledge, plausibility, and climate efficacy outcomes. Knowledge was predicted by individual science interest ($\beta=2.1$, $SE=1.02$, $p=.040$) and hopelessness was negatively predicted by individual science interest ($\beta=-.24$, $SE=.08$, $p=.002$). Utility value predicted plausibility ($\beta=.61$, $SE=.08$, $p<.001$), personal climate efficacy ($\beta=.503$, $SE=.08$, $p<.001$), and collective climate efficacy ($\beta=.61$, $SE=.07$, $p<.001$).

Indirect Effects

I also tested whether the treatment indirectly impacted the main outcomes through any of the significant paths. Namely, I found that, by acting through boredom and individual science interest, the treatment indirectly promoted knowledge ($\beta=.27$, $SE=.13$, $p=.037$) and reduced climate hopelessness ($\beta=-.03$, $SE=.014$, $p=.033$). The treatment also acted through boredom and utility value to indirectly promote plausibility ($\beta=.08$, $SE=.03$, $p=.010$), personal climate efficacy ($\beta=.06$, $SE=.02$, $p=.012$), and collective climate efficacy ($\beta=.07$, $SE=.03$, $p=.010$).

Despite there being no intervention effects on curiosity, I also found that curiosity still indirectly predicted climate change knowledge, plausibility, and efficacy outcomes through motivational processes. Specifically, I found significant indirect effects of curiosity through individual science interest on knowledge ($\beta=.47$, $SE=.24$, $p=.047$) and climate hopelessness ($\beta=-.05$, $SE=.02$, $p=.009$). I also found indirect effects of curiosity through utility value on plausibility ($\beta=.22$, $SE=.06$, $p<.001$), personal climate efficacy ($\beta=.18$, $SE=.061$, $p<.001$), and collective climate efficacy ($\beta=.22$, $SE=.06$, $p<.001$).

Discussion

The purpose of this preregistered study was to test the impact of an online climate change number estimation game on secondary students' learning, motivational, and climate efficacy outcomes. I found that the estimation game conditions significantly improved students' climate change knowledge and situated interest compared with an expository text, and reduced boredom which indirectly influenced plausibility perceptions and climate efficacy outcomes. I also found that knowledge effects were stronger among learners who were more open to reason with belief-discrepant evidence (see Table 4 for a summary of all preregistered hypotheses and results).

[TABLE 4 AROUND HERE]

These findings contribute to the literature in several ways. First, results replicate studies conducted with undergraduate students (Thacker, 2023; Thacker & Sinatra, 2022), but in this case, with a sample of secondary students. Second, results extend prior research by investigating a wider array of emotional and motivational mechanisms that underlie conceptual change processes, specifically identifying the important roles that task value, interest, and epistemic emotions play in such processes. Third, this study explored how a number estimation game can tap into these processes by using urgent, relatable, and action-oriented messages to promote

climate change efficacy. Fourth, despite finding no additional effects of supplementing the game with visualization feedback, null results still have implications for researchers and curriculum designers who wish to improve upon this design in future iterations (Patall, 2021).

In what follows, I discuss the findings and contributions of this research in more detail and consider implications for research and practice.

Intervention Effects on Climate Change Knowledge and Motivation

I found that a climate change number estimation game promoted secondary students' knowledge of the scientific consensus around climate change compared with an expository text ($d=.23$), which is consistent with prior research conducted with undergraduate students (Thacker, 2023; Thacker & Sinatra, 2022). In addition to replicating prior research with secondary students, the current study demonstrated that the game was also successful in promoting situated interest compared with the control. These findings support the idea that shifts in motivation and scientific conceptions tend to happen in tandem, as posited by conceptual change and motivational frameworks (Dole & Sinatra, 1998; Huelleman et al., 2021; Lombardi et al., 2016).

However, despite the effectiveness of the intervention for supporting learning and interest, learners' personal endorsements around whether climate change seems plausible were left unchanged as a result of the intervention, contrary to prediction. Though indirect effects of the intervention on plausibility perceptions were detected (see Indirect Effects section for a more thorough discussion), this lack of a direct effect might be explained by potential ceiling effects due to relatively high baseline levels of plausibility (~ 4.8 of 6) or due to comparatively persuasive information included in the control condition. Similarly, the intervention did not directly promote utility value compared with a control. One possible avenue for amplifying the effects in these regards would be to extend the duration of student engagement with climate

change data and adapt the activity for discursive learning contexts. Researchers and practitioners might consider adapting the estimation game for alternate learning experiences, such as in collaborative classroom learning environments focused on building accurate knowledge about climate change science and its utility for understanding our changing world. In such cases, researchers and practitioners might also consider including assessments that measure learning on deeper levels by incorporating activities that require students to evaluate and synthesize information (e.g., Anderson & Krathwohl, 2001), such as by using a Model-Evidence Link activity to scaffold students' synthesis of multiple forms of evidence (Lombardi et al., 2016c).

Moderating Effects

Results revealed that the effects of the intervention were moderated by several learner characteristics. I found more prominent knowledge effects among students who were willing to reason with belief-discrepant evidence, as consistent with prior research (Thacker, 2023; Thacker & Sinatra, 2022). This evidence provides further support for the idea that adaptive epistemic dispositions are an important factor that facilitate conceptual change processes (Lombardi et al., 2016a), and highlights why curriculum designers and educators should consider emphasizing the importance of being open to reason with belief-discrepant evidence to students.

I also found a moderating effect of math anxiety on plausibility perceptions. Students with higher mathematics anxiety also found climate change to be less plausible, but not among students in the intervention conditions. This finding suggests that negative associations between math anxiety and personal endorsements of climate change may be assuaged with game-like interaction with novel data.

I also found that motivational benefits of the estimation game were greater among students with quantitative expertise and science interest. Students with higher number line

estimation skill received a larger situated interest boost and students with higher individual science interest gained greater utility value boosts from the estimation game. In other words, the game helped learners to see how climate change science could be interesting and useful for their lives, but mostly among students with who were more predisposed to enjoy science and math. Findings from this study thus demonstrate how creating interventions to hold learners' attention by emphasizing how and why content is meaningful can bolster learners' motivation with higher levels of expertise and baseline interest, but choosing attention grabbing activities that trigger situated interest tend to benefit students with lower levels of fluency and interest (Durik et al., 2007).

No Main Effects of Number Line Visualization Feedback

I found that, on average, people assigned to the intervention modified with number-line feedback had no additional learning, plausibility, or motivational benefits compared to the baseline intervention. Though this suggests that there was no significant effect of visualization feedback, such a null finding still contributes to the literature in several ways. One possible explanation for this finding is that simply presenting visualizations without support may not be sufficient to enhance comprehensibility of climate change numbers. This is consistent with evidence suggesting that people require support with basic mathematical skills needed to make meaning from scientific data and data visualizations (Börner, et al., 2016; Peters et al., 2006). Future interventions might incorporate design features that call attention to the visualizations and promote quantitative reasoning strategies that might enhance interpretation of them.

A second potential explanation for this null finding is that the accuracy feedback (i.e., animated stars) provided to students may have been sufficient in signaling discrepancies between their estimates and the scientific values. Future research might isolate and compare the individual

design characteristics presented in this study rather than presenting them in combination, as to test effects of each design element. A third explanation for this finding is that the survey instruments used in this study may not have been sensitive enough to detect more subtle learning or motivational changes resulting the number line feedback. Future research might explore the effects that number-line feedback has on mathematics learning outcomes, such as students' estimation accuracy (c.f., Brown & Siegler, 2001), or might use eye-tracking technology to explore whether and how students coordinate across the various pieces of information provided on the screen (accuracy ratings, quantities, text, and visualizations).

Indirect Effects Through Epistemic Emotions, Interest, and Task Value

Exploratory path analyses revealed that the estimation game significantly reduced boredom, which indirectly predicted motivation and several climate change learning and climate efficacy outcomes. Importantly, all indirect effects of the intervention operated through reductions in boredom. Less boredom predicted greater individual science interest and knowledge, and less climate hopelessness. Less boredom also predicted greater utility value, plausibility, personal and collective climate efficacy. This finding is consistent with academic emotion research suggesting that boredom, which is considered a deactivating and negative emotion, is associated with poorer learning outcomes (Baker et al., 2010; Bench & Lench, 2019; Pekrun et al., 2002). I also found that, although curiosity levels were similar between control and intervention conditions, this emotion was still indirectly predictive of knowledge, plausibility, and efficacy outcomes through individual science interest and utility value. This is consistent with prior research on epistemic emotions inferring that curiosity tends to result from cognitive incongruities that subsequently promote knowledge exploration and learning (Vogl et al., 2019). Taken together, these findings support theory positing that epistemic emotions, interest, and task

value are important mechanisms underlying conceptual change processes (Thacker et al., 2020; Lombardi et al., 2016; Muis et al., 2018). Findings are also consistent with theory predicting that interest and engagement are important intervention mechanisms that can explain motivational and performance outcomes (Hulleman & Harackiewicz, 2021; Seyranian et al., 2023).

As noted, findings revealed that the intervention indirectly supported personal climate efficacy, collective climate efficacy, and reduced climate hopelessness. The estimation game was intentionally designed to provide compelling and coherent quantitative evidence that resonate with students' prior knowledge as well as highlight climate action opportunities. Thus, findings support research suggesting that climate change information is most effective at shifting behavior intentions when it's relatable, emphasizes action opportunities, yet maintains urgency (Stoknes, 2015). Findings also suggest that motivational and emotional processes may be related to such change in behavior intentions.

Path analyses also revealed that the estimation game significantly predicted surprise, an emotion that was not linked directly or indirectly with motivational or climate change knowledge, plausibility, or efficacy outcomes. A potential reason for the disconnected nature of this finding is that surprise is an emotion resulting from observing outcomes that differ from expectation, and can operate along multiple dimensions (e.g., Pekrun et al., 2002; Vogl et al., 2020). For example, a learner with high confidence when estimating a climate change number may report feeling surprised when they discover that they were inaccurate. However, there is no way to know whether this feeling of surprise stems from their unexpectedly low performance or if it pertains to their expectations related to the severity of climate change, or both. Such differences in the object of surprise may predict different learning outcomes. Future research might use qualitative methods in similar contexts to determine *why* students are surprised after

observing true values and determine whether the object of surprise predicts different learning trajectories. More generally, future research might also use qualitative methods to investigate why game-based interventions are capable of promoting learning and motivation by studying the fine-grained genesis of student thinking, such as by using cognitive interviews or design-based approaches (e.g., Desimone & Le Floch, 2007; Hoadley & Campos, 2022; Zengilowski et al., 2021).

Limitations

I acknowledge that this study has several limitations. First, as noted in the Preliminary Analyses section, the experimental conditions were not balanced regarding sample size. There were substantially more students assigned to the condition modified with number line feedback compared to the control or baseline condition, which may have reduced power. Second, other than intervention effects, the variables represented in the exploratory path model do not necessarily represent causal or longitudinal relationships and should be interpreted instead in terms of associations between variables. Future research might consider using longitudinal research designs to establish episodic relationships between variables. Third, while experimentally manipulating intervention variants allowed for the detection of number-line specific effects in addition to the game's baseline features, such manipulations made it difficult to disentangle the unique effects of each design element isolated from interactions with other features. Future research might isolate specific effects of providing number-line feedback rather than presenting it in combination with multiple other features. Fourth, experiments have distinct tradeoffs regarding external validity. On the one hand, randomized experiments enable causal inferences about the effects of learning interventions, but on the other hand, such study designs can require that students complete the learning experience individually rather than in a classroom

setting. This is beneficial for identifying intervention effects, but makes it difficult to know whether the intervention would have similar effects in a naturalistic classroom setting. Future studies might adapt this intervention for classroom settings, such as by assessing its use to foster classroom discussions about climate change.

Implications

This study contributes to theory and practice. Findings support relationships hypothesized by theories of conceptual change (Dole & Sinatra, 1998; Lombardi et al., 2016), motivation (Hulleman & Harackiewicz, 2021) and climate change psychology (Stoknes, 2015) with a secondary student sample. The study also explored the extent to which mathematical reasoning skills might support science learning (Siegler, 2016), and resulted in an online intervention that can be easily shared online with teachers and students.

This study also explored indirect relationships between exposure to novel data and people's emotion, motivation, and climate change efficacy. Results revealed that novel data, when presented in an urgent yet hopeful manner, can shape people's learning, motivation, and intent to act on climate change. Such an intervention provides researchers and instructors with the means to increase student understanding and climate change efficacy, properties of curriculum that are important, but infrequently implemented in the USA (Cho, 2023). This study also explored the indirect effects of the game, revealing that boredom, science interest, and utility value may represent important mechanisms involved in conceptual change processes.

This research showcases an open-access online learning intervention that can be easily implemented with secondary students to promote learning, motivation, climate efficacy, and math-science integration. Teachers, curriculum designers, and researchers might be encouraged to adapt this intervention for classroom contexts, while emphasizing to students the important

role of being open to scientific evidence, even when that evidence may not agree with their existing beliefs. Indeed, researchers argue that epistemic dispositions are malleable (Stanovich & West, 1997), particularly among adolescents who are in a prime position in their development to see the value of being open-minded, given that they tend to be less settled in their beliefs and values when compared with adults (Emlen-Metz et al., 2020). And while evidence is only emerging that Actively Open Minded Thinking can be changed (Perkins, 2019; 1986; Gurcay-Morris, 2016), some findings suggest that openness is correlated with classroom characteristics such as course content, pedagogy, uncertainty, personal relevance, and task challenge (Cheng & Wan, 2017). Researchers, curriculum developers, game designers, and practitioners might thus consider pursuing the creation of science learning environments that encourage learners to openly reason with new evidence.

Creating engaging experiences for students to interact with novel data can be a useful approach for teaching about socio-scientific topics and for bolstering learning, motivation, and intended action. The conceptual change principles embodied in the estimation game might thus be relevant for practitioners, curriculum developers, and intervention designers who aim to communicate information about socio-scientific topics that have specific psychological barriers. Indeed, this study shows how learning experiences can be created to engage students with comprehensible, compelling, and valid information as a means to support positive emotions, motivation, and conceptual change, while also helping learners overcome psychological barriers by communicating urgent yet hopeful and action-oriented messages. By expanding curricular resources and implementing more effective learning tools in and out of the classroom, researchers and practitioners need not feel helpless about the state of climate change education and can take action to advocate for progress.

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Appendix A. Examples of Experimental Conditions

Estimation Game Intervention Group.

Question 1 out of 12

What is the change in the level of methane (a greenhouse gas) in the atmosphere from 1750 until now?

% Increase ▼ in Level of Methane

SUBMIT ANSWER

a. Participants estimate a climate change quantity.

Amazing Job!

★ ★ ★ ★ ★

151% increase in atmospheric methane levels

Methane comes from things like trash in landfills and cow manure from dairy farms, and it can stay in the air for many years. To lower the amount of methane in the air, we can reduce waste and eat less meat.

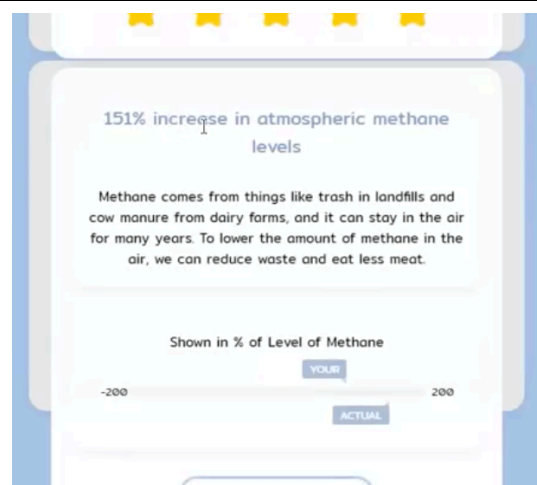
NEXT QUESTION

▼ Display Sources

b. A popup window displays the scientifically accepted value, along with their original estimate, an explanation, sources, and accuracy feedback.

Estimation Game + Visualization Group.

c. After estimating the climate change quantity, the popup window displays the same information as the baseline intervention, but with an added number line visualization.



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

THE ENHANCED GREENHOUSE EFFECT

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

Note. Use this link to access the estimation game used in this study <http://ianthacker.com/design.html>. To access the complete set of intervention and control texts, as well as all survey items, see the supplemental materials: <https://osf.io/e4gcd/>

Appendix B. Hypotheses and Findings

Preregistered Research Question	Findings
I hypothesized (H1) that students assigned to the intervention conditions will have greater knowledge, situated interest, utility value, and find climate change to be more plausible at posttest when compared with those assigned to read an expository text.	<p>✓ Posttest knowledge was significantly higher in the intervention conditions compared with the control ($d=.23, p=.020$).</p> <p>✓ Situated interest was significantly higher in the intervention conditions compared with the control ($d=.30, p=.030$).</p> <p>✗ Intervention conditions were not significantly different to the control with regards to utility value or plausibility (all $ps>.385$).</p>
I hypothesize (H2) that supplementing the intervention with number line visualization feedback will support (H2.1) climate change knowledge, (H2.2) plausibility, and (H2.3) situated interest compared with those who are assigned to the intervention but without the visualization feedback. (H2.4) I expect no significant differences in utility value between these conditions.	<p>✗ No significant differences in knowledge, plausibility, situated interest ($ps>.263$)...</p> <p>✓ ...or utility value ($p=.685$).</p>
I hypothesized (H3) that effects will be stronger among people with higher levels of (H3.1) adaptive epistemic dispositions, (H3.2) number line knowledge, (H3.3) individual science interest, and (H3.4) weaker among people with math anxiety.	<p>✓ I found significant moderating effects of adaptive epistemic dispositions on knowledge ($\beta=.216, p=.044$), math anxiety on plausibility ($\beta=-.110, p=.045$), individual science interest on utility value ($\beta=.276, p=.006$), and number line skill on situated interest ($\beta=.331, p=.017$).</p> <p>✗ No additional moderating effects were found (all $p>.068$).</p>
Exploratory Research Question	
RQ5—Will there be indirect effects of the intervention through epistemic emotions and motivational variables?	<p>By acting through boredom and individual science interest, the treatment indirectly promoted knowledge ($\beta=.27, SE=.13, p=.037$) and reduced climate hopelessness ($\beta=-.03, SE=.014, p=.033$). The treatment also acted through boredom and utility value to indirectly promote plausibility ($\beta=.08, SE=.03, p=.010$), individual climate efficacy ($\beta=.06, SE=.02, p=.012$), and collective climate efficacy ($\beta=.07, SE=.03, p=.010$).</p>

Note. “✗” indicates hypotheses that are not supported, “✓” indicates hypotheses that are. The official preregistration can be accessed using the following link: <https://osf.io/tncx3>

Table 1.*Descriptive Statistics by Condition and Intercorrelations for All Analytic Variables (N=248)*

	Total							Control		Game		Game+NL		Correlations																		
Variable	M	SD	Min	Med	Max	Items	α	M	SD	M	SD	M	SD	pre.kn	post.kn	pre.pl	post.pl	anx	aot	est	su	cu	ex	co	an	fr	bo	p.eff	c.eff	hpls	ind.int	sit.int
Knowledge Pretest	3.8	0.5	2.3	3.9	4.9	7	.59	3.8	0.5	3.8	0.6	3.7	0.5																			
Knowledge Posttest	4.0	0.6	1.9	4.0	5.0	7	.76	3.9	0.6	4.1	0.7	3.9	0.6	.74***																		
Plausibility Pretest	4.8	1.2	1.0	5.3	6.0	4	.77	4.7	1.3	5.0	0.9	4.8	1.1	.58***	.66***																	
Plausibility Posttest	5.0	1.2	1.0	5.5	6.0	4	.83	4.8	1.3	5.2	1.2	4.9	1.2	.57***	.73***	.84***																
Math Anxiety	2.9	1.0	1.0	2.9	5.0	9	.93	3.1	1.1	2.7	1.0	2.8	1.0	-.13*	-.20**	-.12	-.11															
Active Open-Minded Thinking	4.8	0.9	2.4	4.9	7.0	7	.72	4.9	0.9	4.9	0.9	4.7	0.9	.28***	.43***	.44***	.44***	-.08														
Number Line Estimation Skill	6.5	2.4	1.0	7.0	12.0	12	.64	6.4	2.5	6.5	2.3	6.5	2.4	.29***	.39***	.34***	.35***	-.37***	.33***													
Surprise	3.0	1.2	1.0	3.0	5.0	1	-	2.7	1.1	3.2	1.2	3.0	1.1	.02	.10	.16*	.23***	.07	.16*	.08												
Curiosity	3.5	1.0	1.0	3.0	5.0	1	-	3.4	1.0	3.4	1.1	3.5	1.0	.18**	.30***	.38***	.41***	.02	.33***	.10	.41***											
Excitement	2.4	1.1	1.0	2.0	5.0	1	-	2.2	1.1	2.4	1.2	2.3	1.1	-.26***	-.27***	-.16*	-.19**	.07	-.18**	-.11	.22***	.16*										
Confusion	2.4	1.2	1.0	2.0	5.0	1	-	2.6	1.3	2.3	1.2	2.3	1.1	-.19**	-.23***	-.11	-.10	.31***	-.10	-.24***	.30***	.18**	.39***									
Anger	2.9	1.3	1.0	3.0	5.0	1	-	2.9	1.3	2.9	1.4	2.9	1.2	.10	.05	.14*	.15*	.33***	.14*	-.10	.26***	.27***	-.01	.41***								
Frustration	2.9	1.3	1.0	3.0	5.0	1	-	2.9	1.3	3.0	1.5	2.8	1.3	.18**	.13*	.17**	.19**	.26***	.13*	-.04	.18**	.29***	-.07	.31***	.66***							
Boredom	2.4	1.3	1.0	2.0	5.0	1	-	2.9	1.3	2.1	1.2	2.2	1.2	-.39***	-.47***	-.40***	-.38***	.24***	-.23***	-.23***	-.18**	-.23***	.16**	.26***	-.02	-.01						
Personal Climate Efficacy	4.9	1.2	1.0	5.0	7.0	3	.72	4.8	1.2	5.0	1.2	4.9	1.1	.43***	.43***	.53***	.56***	-.04	.23***	.19**	.31***	.32***	.02	-.01	.14*	.24***	-.28***					
Collective Climate Efficacy	5.2	1.1	1.8	5.4	7.0	5	.81	5.2	1.0	5.4	1.1	5.1	1.0	.48***	.49***	.62***	.68***	-.08	.30***	.28***	.25***	.35***	-.04	.00	.17**	.23***	-.31***	.62***				
Climate Hopelessness	3.6	1.3	1.0	3.7	7.0	3	.70	3.8	1.2	3.3	1.5	3.6	1.2	-.29***	-.38***	-.24***	-.24***	.19**	-.31***	-.27***	-.01	-.05	.25***	.28***	-.05	-.08	.31***	-.23***	-.24***			
Individual Science Interest	5.1	1.4	1.0	5.2	7.0	3	.77	5.0	1.4	5.1	1.5	5.2	1.3	.34***	.43***	.47***	.43***	-.20**	.34***	.28***	.18**	.35***	-.05	-.07	.12	.17**	-.31***	.44***	.40***	-.25***		
Situated Interest	5.3	1.3	1.0	5.3	7.0	4	.85	5.0	1.4	5.5	1.2	5.3	1.3	.36***	.45***	.51***	.56***	-.02	.24***	.16*	.32***	.49***	.10	.03	.26***	.23***	-.44***	.54***	.59***	-.12	.55***	
Utility Value	5.5	1.2	1.5	5.8	7.0	3	.86	5.6	1.0	5.5	1.1	5.4	1.2	.50***	.57***	.64***	.68***	-.03	.33***	.25***	.28***	.49***	-.03	.02	.25***	.28***	-.32***	.63***	.70***	-.16*	.58***	.75***

Note. Control = Control condition where participants read an expository text ($n=64$), Game = Estimation Game intervention where participants estimated 12 climate change numbers before being shown the true value ($n=53$), Game+NL = Estimation Game intervention supplemented with number line feedback ($n=131$). * $p<.05$; ** $p<.01$; *** $p<.001$

Table 2.

Effects of The Estimation Game Conditions on Posttest Knowledge, Plausibility, Situated Interest, and Utility Value and Moderating Effects of Math Anxiety, Actively Open-Minded Thinking, Individual Science Interest, and Number-Line Accuracy (N=248).

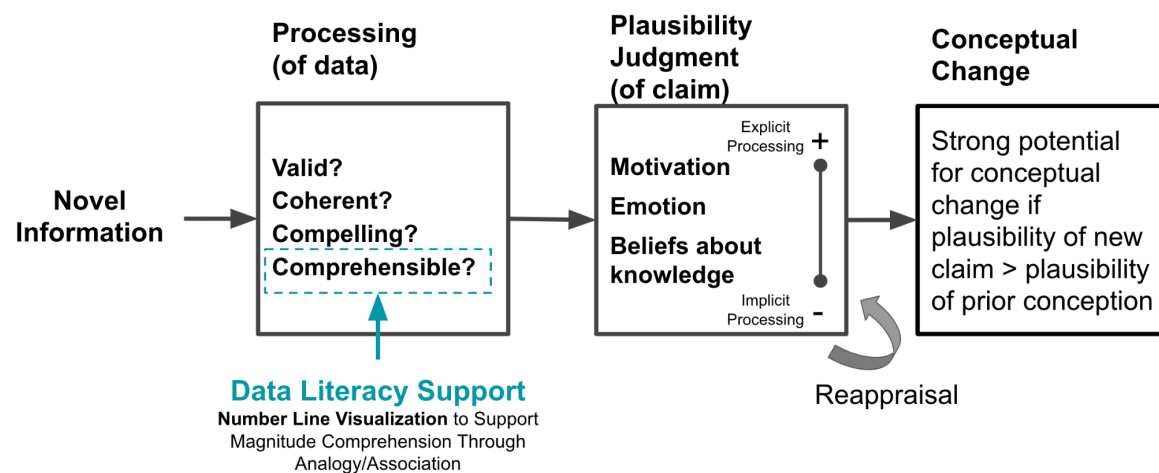
	Dependent variable:									
	Knowledge					Plausibility				
	No Moderator	Math Anxiety as Moderator	AOT as Moderator	Individual Science Interest as Moderator	Number-Line Estimation Skill	No Moderator	Math Anxiety as Moderator	AOT as Moderator	Individual Science Interest as Moderator	Number-Line Estimation Skill
Intervention Conditions	.208*	.196*	.219**	.191*	.200*	.009	-.007	.021	.012	.010
Conditions	(.085)	(.083)	(.084)	(.081)	(.079)	(.069)	(.068)	(.070)	(.067)	(.067)
	p = .016	p = .019	p = .010	p = .019	p = .012	p = .901	p = .919	p = .768	p = .862	p = .889
Moderator		-.017	.079	.103	.221***		-.092*	.056	-.008	.096*
		(.055)	(.097)	(.076)	(.059)		(.038)	(.050)	(.058)	(.042)
		p = .753	p = .416	p = .181	p = .0003		p = .017	p = .265	p = .887	p = .023
Intervention * Moderator		-.112	.216*	.128	-.039		.110*	.042	.078	-.033
		(.074)	(.106)	(.088)	(.073)		(.054)	(.057)	(.068)	(.066)
		p = .131	p = .044	p = .146	p = .600		p = .045	p = .466	p = .251	p = .621
	Situated Interest					Utility Value				
Intervention	.294*	.288*	.303*	.235~	.294*	-.144	-.166	-.124	-.206~	-.151
	(.149)	(.141)	(.147)	(.138)	(.148)	(.134)	(.129)	(.128)	(.115)	(.130)
	p = .050	p = .043	p = .040	p = .089	p = .048	p = .283	p = .198	p = .332	p = .076	p = .248
Moderator		-.037	.060	.368**	-.088		-.111	.234*	.377***	.122
		(.128)	(.130)	(.112)	(.120)		(.106)	(.104)	(.080)	(.098)
		p = .773	p = .644	p = .002	p = .464		p = .299	p = .026	p = .00001	p = .214
Intervention * Moderator		.048	.245	.232~	.331*		.101	.130	.276**	.178
		(.148)	(.150)	(.127)	(.137)		(.134)	(.130)	(.099)	(.120)
		p = .746	p = .103	p = .068	p = .017		p = .454	p = .317	p = .006	p = .141

Note: All coefficients are standardized around the mean. AOT=Actively Open-Minded Thinking. The comparison group to the intervention predictor is the control condition in which participants read an expository text about the greenhouse effect. Pretest scores are included as covariates when applicable, though not shown in the table. Namely, pretest knowledge is a covariate when knowledge is the outcome and pretest plausibility when plausibility is the outcome. Boldfaced values indicate significant or marginally significant results for predictors at the $p < .1$ level.

~ $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$

Figure 1.

Conceptual Change Process Model Utilized in This Study.



Note. This conceptual change model was inferred from Dole & Sinatra (1998), Lombardi et al., (2016), and Siegler (2016).

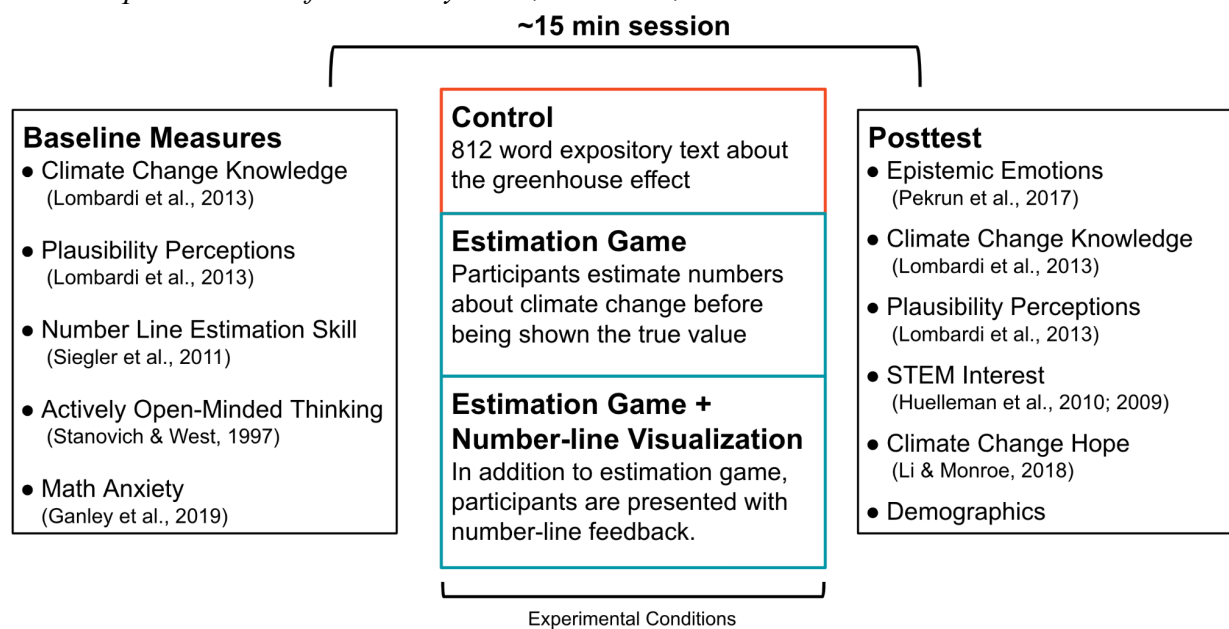
Figure 2.*Visual Representation of the Survey Flow, Materials, and Procedures*

Figure 3.

Hypothesized Model Depicting Indirect Effects of the Intervention through Emotional and Motivational Processes

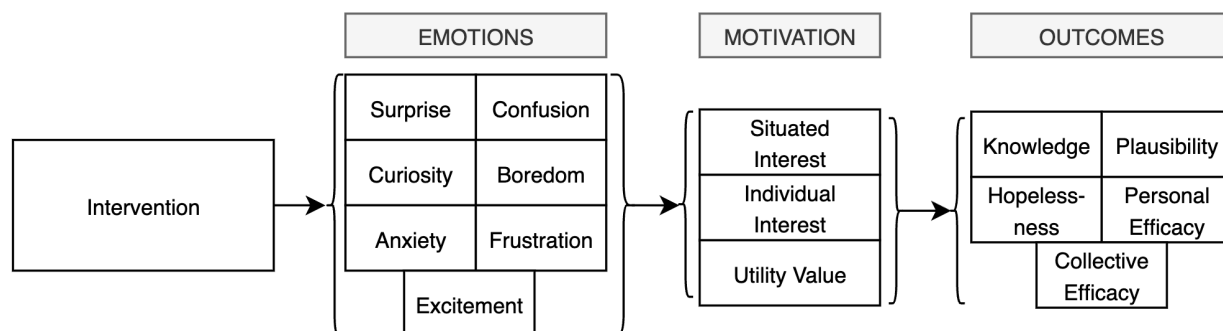
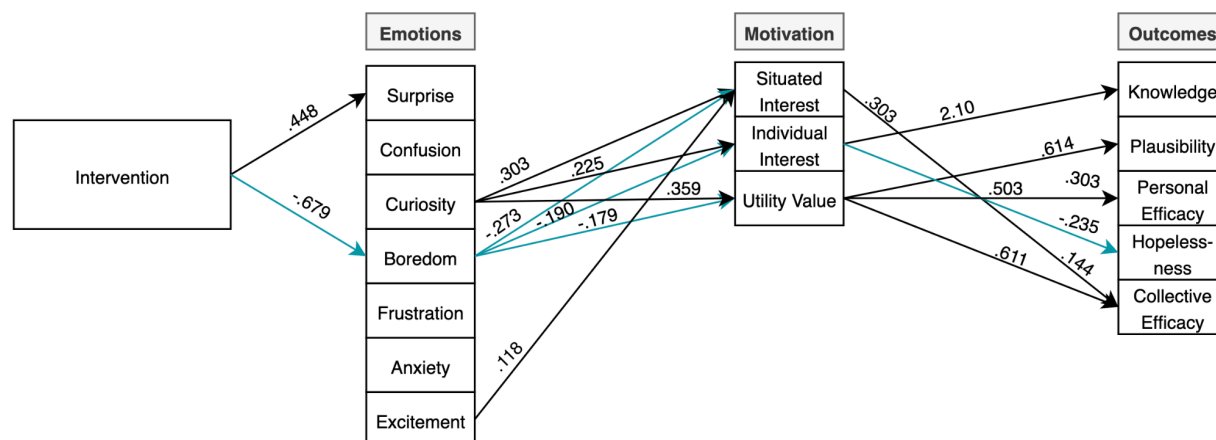


Figure 4.
Path Model with Significant Paths Shown



Note. Only paths that are significant at the .05 level or below are shown. Blue paths are used when coefficients are negative. All variables shown represent values at posttest. Not shown are intercorrelations between emotion variables, motivation variables, and outcome variables.