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A Number Estimation Game to Promote Secondary Students' Data Literacy and Affective Engagement With Climate Change Data

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Abstract

Scientific data and data visualizations can communicate critical information about issues of environmental sustainability and climate change to the general public. While climate change is a pressing sustainability challenge and a topic of concern to many young people, it is poorly covered in academic standards and is a difficult topic for students to learn due to the complexity of the supporting data and emotionally charged nature of the evidence of climate change. This design-based research project reports on the design and refinement of an online, game-based intervention using number-line data visualizations, with a focus on understanding and supporting how students comprehend and emotionally engage with climate change data. Over the course of three design iterations, we engaged 12 racially diverse secondary students in the U.S. in think-aloud interviews and documented design revisions. Survey data revealed significant growth in scientific knowledge from pretest-to-posttest. Qualitative, inductive analyses of interview transcripts revealed dimensions of students' *quantitative reasoning strategies* when engaging with data (students drew on prior knowledge, employed mental computation, used proportional reasoning, and wildly guessed), and *emotional engagement* (students expressed surprise, anxiety, relief; sometimes about climate change, sometimes about their performance). Findings (a) illustrate how reasoning with data in game-based contexts can strengthen both mathematical understanding and climate change awareness, (b) contribute to the idea that emotion is an integral component of data-driven learning of socioscientific issues of sustainability, and (c) demonstrate how design features can be refined to connect quantitative reasoning, emotion, and sustainability-oriented mathematics learning.

Introduction

In efforts to reshape school experiences to center urgent, complex, interdisciplinary and politically relevant issues (Andersson & Barwell, 2021), it is important to offer students opportunities to apply their mathematical knowledge and skills to make sense of and take action on relevant and timely topics. *Socioscientific topics*—topics that center on pressing real-world, ethically and socially relevant issues—can be viewed through the lens of mathematics to enhance student interest, interdisciplinary thinking, perceived relevance of mathematics, and foster critical consciousness and civic advocacy for change (Sinatra & Hofer, 2021; Sadler et al., 2007; Authors, 2025). In particular, anthropogenic climate change and its impact on biodiversity loss, extreme weather, climate migration, and water and food insecurity, is a socio-ecological sustainability threat facing humanity that deserves attention in classrooms—both in terms of helping students understand *conceptually* difficult content and to process our *emotionally* difficult reality.

Climate change is *conceptually* difficult, partly because evidence of climate change relies heavily on quantitative data. Secondary students generally have few opportunities to critically evaluate and interpret socio-scientific data (Alrø et al., 2010; Andersson & Barwell, 2021; Carlson & Johnson, 2015; Gould, 2017, Risdale et al., 2015, Rubel et al., 2021, Weiland, 2017), and when they do, they often encounter challenges in making meaning of data and data visualizations (Vahey et al., 2012; Doyle et al.,

2015; Peters et al., 2006; Siegler, 2016; Vamvakoussi & Vosniadou, 2004, 2007, 2010). For example, secondary students sometimes struggle to understand and compare number magnitudes and when using conventional linear number line visual representations (Doyle, 2015; Vamvakoussi & Vosniadou, 2004; 2007; 2010), and an inability to use visual representations to compare magnitudes of rational numbers (e.g., fractions and decimals) can stifle numerical development, academic achievement, and contribute to misinterpretations of science topics (Sasanguie et al., 2012; Siegler et al., 2012; Siegler, 2016). Without supporting students' quantitative reasoning skills and providing frequent opportunities for students to reason with data about socioscientific topics, student understanding about critical sustainability issues like climate change can fall by the wayside.

Furthermore, climate change can be an *emotionally* challenging topic. Unlike traditional classroom topics, learning about climate change can evoke *strong emotions* including, climate-anxiety or indignation, that can either hinder or promote engagement with scientific ideas (Authors, 2025; Herrick et al., 2025; Stoknes 2015; Wray, 2023). Negative emotions and climate-anxiety—defined as feelings of distress, fear, and worry about the climate crisis—can become paralyzing barriers to learning (Stoknes, 2015; Wray, 2023). Learning about climate threats to human existence can inspire a sense of doom associated with seemingly apocalyptic global problems, leading learners to disengage from the topic out of self-protection, thus interrupting the processing of information and motivation that is crucial for learning (Sinatra & Hofer, 2021; Stoknes, 2015; Wray, 2023). As such, there is a need to create climate change learning contexts that dually support conceptual understanding and data literacy (quantitative-competencies that facilitate decision-making; Carlson & Johnston, 2015; Risdale et al., 2015) and affective engagement in mathematics classrooms.

There are several approaches that support climate change learning through data investigation (Herrick et al., 2025; Steffensen, & Kacerja, 2021), and micro-interventions that present people with surprising numbers about climate change after they estimate those numbers (Ranney & Clark, 2016; Authors, 2022; Authors, 2024b). However, despite evidence documenting the effectiveness of data-oriented approaches to climate change instruction, few studies have explored the possibility of using game-based learning experiences for climate change learning, tested their efficacy with secondary students, or assessed the role of affect and emotions in learning processes therein. Game-based approaches to climate learning have the potential to position students' quantitative reasoning skills as critical for in-game progression and to enhance affective engagement to support students in overcoming climate-related anxieties (Spyckerelle, 2022).

The purpose of this project was to develop a learning intervention for promoting secondary students' climate change data investigations using a game-based approach. The curricular design is guided by an evolving theoretical model of integrated STEM teaching and learning centered on promoting Data Literacy for Conceptual Change (i.e., the DLCC model). In what follows, we describe this model, document our process of designing a game-based online intervention using the DLCC model, and investigate the breadth of reasoning strategies students use and the emotions they demonstrate within the game and throughout the learning process.

Theoretical Framework

In the effort to address conceptual and affective barriers to learning, we draw from a theoretical model of integrated STEM teaching and learning, the Data Literacy skills for Conceptual Change (DLCC) model (Authors, 2025). The DLCC positions key data literacy skills identified in mathematics education research as essential tools for supporting scientific conceptual change. To frame how climate data can support science learning, we introduce the DLCC after describing two supporting frameworks: conceptual change and critical data literacy.

Conceptual Change

Conceptual change is a process where individuals restructure their conceptual knowledge to be more aligned with experts after engaging with novel information (Dole & Sinatra, 1998; Lombardi et al., 2016; Murphy & Mason, 2006). Several theories of conceptual change posit that novel information, such as data and data visualizations, can be the catalyst for such shifts in conceptions (Dole & Sinatra, 1998; Lombardi et al., 2016; Posner et al., 1982). In these conceptual change models, learner characteristics (e.g., *beliefs*, *motivation*, and *emotions*) and information characteristics (e.g., *comprehensibility*, *compellingness*, *source credibility*, and *relevance*) interact to determine cognitive engagement. Higher levels of engagement, along with shifts in motivation and emotion, predict more serious consideration (or reconsideration) of whether scientific ideas are *plausible* (Lombardi et al., 2016), and higher likelihood of conceptual change. Of these many factors, evidence suggests that bolstering *comprehensibility* and *compellingness* of data and data visualizations can bolster student engagement and conceptual change (Authors, 2022; 2024a, 2024b; 2025).

Data Literacy

While conceptual change research offers insight into how novel information can trigger key learning processes, there are important factors to consider when that information is quantitative. In order for a student to comprehend data and find it compelling, they must have certain competencies specific to data interpretation, also called *data literacy*. Though there is no consensus on a definition, the term “data literacy” can be defined as the statistical competencies, methods, and techniques that facilitate decision-making (Gould, 2017). These include: *acquiring*, *managing*, *visualizing*, *interpreting*, *evaluating*, *reading*, and *using* data (Börner et al., 2019; Carlson & Johnston, 2014; Kim et al., 2023; Prado & Marzal, 2013; Ridsdale et al., 2015); dimensions that are critical to advancing science (Qiao et al., 2024). A central skill that cuts across these competencies is *proportional reasoning*. For example, Vahey et al. (2012) showed that when teachers were shown to use a curriculum involving the use of proportional reasoning to make sense of cross-disciplinary data, secondary students in their classes showed significantly greater gains in data literacy, math, and science learning compared to business-as-usual classrooms.

Critical data literacy is also an important aspect of data literacy, particularly when engaging with socio-scientific data pertaining to issues of sustainability. Critical data literacy includes skills such as: *reformatting* (questioning what and how data is quantified), *reframing* (questioning relationships depicted and visualized), *renarrating* (questioning the stories authors tell), and *writing* data (using statistics to communicate and argue with data; Rubel et al., 2021; Weiland; 2017). These critical data-literacy perspectives stem from a wider tradition of *critical mathematics* that build from the ideas of Freire (2007), in which mathematics is viewed as a tool to empower students to critically analyze society and to read and transform the world (Andersson & Barwell, 2021; Gutstein, 2006). In this way, mathematical competencies can be applied to make sense of socio-scientific data and to foster scientific knowledge, engagement, and feelings of efficacy to address climate change (e.g., Author, 2025; Authors, 2024b).

Quantitative Reasoning Strategies for Numerical Estimation

As noted, data literacy encompasses multiple competencies related to data-based decision-making. In this study, we assessed the quantitative reasoning processes students use when considering and estimating data. Namely, we focus on leveraging students' proportional reasoning skills for numerical estimation of socio-scientific numbers. For example, when students are asked to estimate a quantity (e.g., the global mean sea level rise in the last 20 years), they might use a given baseline quantity (e.g., that the sea level rose 1 inch from 1900 to 1920) to better estimate the unknown value. Doing so requires students to recognize the multiplicative relationship between time and change, scale the baseline rate based on prior knowledge and beliefs, and coordinate units across quantities to generate a proportionally justified estimate (Ranney et al., 2001; Van De Walle et al., 2013). Such applications of proportional reasoning are important, partly for increasing estimation accuracy, but more critically, for helping students process the meaning of the number magnitudes (e.g., inches of sea level rise) and consider their relationships with scientific explanations (e.g., global climate change; Authors, 2024a, Siegler, 2016; Ranney & Clark 2016). When students have estimated a quantity and are then presented with the scientifically accepted value (3 inches of sea level rise in the last 20 years), the feedback may shift their thinking—both in terms of their quantitative knowledge and their perceptions of climate change as a plausible explanation for sea level rise.

Such connections between numbers and their referents can also be facilitated by the use of data visualizations. A particularly useful visualization for representing climate change numbers is the linear number line, which depicts number magnitudes on a line using a linear scale. The number line is widely considered 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 the 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).

The Data Literacy for Conceptual Change (DLCC) Model.

Data literacy frameworks and conceptual change share many common goals and approaches to inform and empower students on issues of climate change and sustainability. To synthesize across these perspectives and explicitly clarify our theoretical stance and approach to curricular design, we draw from the Data Literacy for Conceptual Change (DLCC) model (see, Authors, 2025). This emerging model assumes that key data literacy skills (e.g., such as proportional reasoning, interpreting, framing, narrating data) help students comprehend and make personal meaning of data, and that these intersect with the affective dimensions (e.g., motivation, emotion, beliefs) that promote conceptual change (see Fig. 1).

[Figure 1]

Specifically, this model assumes that (a) *data properties*, such as the formatting, scales, and embedded narratives of data and data visualizations influence learners' (b) initial *perceptions of the data* in terms of its validity, coherence, compellingness, and comprehensibility—the latter being shaped by individuals mathematical reasoning skills. These initial perceptions subsequently predict learners' (c) plausibility appraisals and *processing of scientific claims*, ideas, and explanations represented by the data, and ultimately their (d) negotiation of whether to adopt such scientific conceptions and experience *conceptual change*. We also assume that scientific ideas are considered more thoughtfully and explicitly when learners are *motivated* and engaged, and that critical reconsiderations of the data are key processes that initiate reappraisals and renegotiation of scientific ideas. In this way, the DLCC assumes that scientific conceptual change is most likely to occur when properties of data are appropriate for learners' data interpretation skills, and that learners are motivated, engaged, and given opportunities to critically engage with data.

Key evidence-based practices aligned with the DLCC model are: *selecting appropriate data* for instruction that meet students' data comprehension levels, *promoting students' data comprehension skills* (such as by building up students' proportional reasoning skills and interpretation of graphical conventions), *motivating student learning* by selecting relevant, meaningful datasets that support student curiosity, and offering opportunities for *critical reflection* and reconsideration of the data and data representations.

Evidence supports relationships posited by the DLCC. For example, prompting secondary and undergraduate students who were randomly assigned to estimate key climate change numbers before being shown the consensus value, tend to improve their climate change knowledge compared with a control group by about a third of a standard deviation (Ranney & Clark, 2016; Authors 2022; 2023; 2024b). Additional qualitative and experimental evidence demonstrates that these learning outcomes are bolstered with targeted support of proportional reasoning strategies and by providing compelling and contextualized data narratives (Authors, 2023; Authors, 2024a). Further, efforts to support data comprehensibility, validity, and compellingness were found to be either moderated or mediated by learners' adaptive beliefs about knowledge, emotions, and motivational factors (Authors, 2023; 2024a; 2024b; 2025b). These studies reveal the importance of attending to both mathematical and scientific learning properties when designing instruction and begin to illustrate the benefits of intentionally

mitigating negative emotion and climate hopelessness when discussing climate change (see Stoknes, 2015). Indeed, explicit attention to learners' emotional responses can bolster students' engagement with climate-related data and support conceptual change. For example, Herrick et al. (2025), found that, by weaving affective dialogue into data literacy instruction, teachers were able to support students in processing climate-related emotions while creating a shared sense of urgency and curiosity around local climate impact, which support the DLCC model's emphasis on individual learners revisiting and revising their prior conceptions.

Yet, despite the emerging evidence for this theoretical model, there are several components of the model that require further empirical support. For example, little to no research has attempted to enhance learning that occurs from novel scientific numbers by developing game-based estimation tasks that integrate conventional number line representations, nor assessed how such interventions would enhance data comprehensibility, and scientific conceptual change. Furthermore, while quantitative research studies have identified climate-centered emotions as an important factor involved in the processing of scientific claims about climate change (e.g., Authors, 2024b), few if any qualitative studies have investigated *how* students emotionally engage with climate change data. For example, exploring the object of students' emotions (e.g., about performance or about the devastation of climate change) may indicate important nuances in how and why emotions are relevant for learning. Additionally, of the few studies investigating estimation of socio-scientific quantities with secondary students (e.g., Munich et al., 2007), none utilize visualizations nor focus specifically on supporting climate change learning.

Current Study

The current study addresses these gaps in the research by adopting a curricular design approach that elicits student perspectives and feedback to guide the process of designing learning technology. Namely, we designed an online number estimation game intended to present secondary students with novel data and data visualizations about climate change and evaluated the effectiveness of the design while examining student learning processes and emotional responses to the data. The game is structured to position mathematical skills as a key in-game strategy to advance game progress and to help alleviate climate anxiety associated with learning about global devastation. We address the following research questions:

- **Research Question 1 (RQ1)**: How can a game-based learning intervention be developed that leverages data-literacy skills for the learning of climate change science?
- **Research Question 2 (RQ2)**: How do secondary students reason with and emotionally engage with climate change data in this online game?

Methods

Design-Based Research

To answer these research questions, we used a design-based research (DBR) methodology (e.g., Anderson & Shattuck, 2012; Hoadley & Campos, 2022) to guide the design of an online intervention that we call the "Estimation Game." DBR is an approach to both improving teaching and learning and generating theory by designing, testing, and refining instructional interventions. Through iterative cycles of design, implementation, observation, and analysis, DBR intends to both revise and improve on instructional designs and generate explanations for what these design decisions reveal about how students learn (Anderson & Shattuck, 2012; Hoadley & Campos, 2022). Typical of DBR, our intervention's design, implementation, and revision occurred over several iterations as guided by student input and reflection on emerging conjectures about teaching and learning (Bakker, 2019; Cobb et al., 2003).

The Estimation Game

We began our investigation by revising a pre-existing online estimation game (Authors, 2024a). In this prior study, undergraduate students completed a tutorial activity introducing them to the process of estimating quantities before being shown the true value, along with tips and strategies for improving accuracy: rescaling given values to better estimate unknowns, rounding values prior to mental computation, and tolerating estimation errors. Then, they were asked to estimate 12 numbers about climate change before being presented with the scientifically accepted value in a game-based web app. Half of these estimation prompts included "hints," or given benchmark values that might be rescaled to estimate the unknown values with greater accuracy. The scientifically accepted climate change number appeared in a pop-up window accompanied by estimation accuracy feedback in the form of one to five "gold stars," a short explanation of the climate change number to help students contextualize the quantity in terms of students' prior knowledge, and links to sources of the information to improve source credibility.

For the current study, we aimed to modify this baseline design to be more appropriate for secondary students and to improve data comprehensibility and affective engagement. We modified the original game to (a) present additional personalized feedback in the form of a number line visualization displaying the students' estimate in comparison with the scientifically accepted value, (b) include in-game text that is at the reading level of secondary students, and (c) revise the look and feel of the game to be more game-like and approachable (see findings for details). This work resulted in an online, open-source number estimation game for secondary students with number line visualization feedback that can be easily shared with the general public online (see the Supplemental materials SE–SG for game content).

Participants and Procedure

As is characteristic of design-based research, the design, implementation, and revision of the intervention occurred over several iterations (Anderson & Shattuck, 2012). Over the course of three design iterations, the lead author and two graduate research assistants conducted 12 one-on-one

cognitive “think aloud” interviews (Desimone & Le Floch, 2004) via Zoom with a convenience sample of secondary students (grades 7–12) in a diverse metropolitan city of a southwestern state in the USA. Students identified as female (50%), male (50%), Hispanic (60%), White (58%), two or more races (33%), and Black (8%). The first and second design iteration both consisted of five interviews, and the third iteration consisted of two.

While “thinking aloud,” students (a) completed a pretest of climate change knowledge and plausibility perceptions, (b) engaged with the estimation game, and (c) completed a posttest identical to the pretest along with a demographics questionnaire. Afterward, students were prompted to answer four questions about the nature of their experience, such as “What would you change about the look and feel of the app?”, “Is there anything you can think of to make the game more engaging or fun?” and “What would you change about the way information is presented in this game?” The full interview protocol is presented in Appendix SA and SB in the Supplementary Materials.

Survey Materials

At pretest and posttest, students completed survey measures of climate change knowledge and plausibility. The knowledge measure consisted of 7 items measuring students’ knowledge of the scientific consensus on climate change adapted from Lombardi et al. (2013). Students responded using a five-point agreement scale to indicate “...the degree to which you think that *climate scientists* agree…” with statements such as, “The average sea level is increasing. This is evidence of climate change.” The plausibility perceptions measure consisted of 4 items measuring personal endorsements related to human-induced climate change adapted from Lombardi et al. (2012). Students responded using a seven-point plausibility scale—ranging from 1 = greatly implausible (or even impossible) to 6 = highly plausible—regarding statements such as “Human influences on climate include rising sea levels and melting of snow and ice.” Participants also completed a demographics questionnaire at posttest. Surveys are presented in Appendix SC and SD in the Supplementary Materials. Scales at pretest and posttest were internally reliable at conventional levels when (McDonalds Omega: $\omega_{plausibility_pre} = .92$, $\omega_{plausibility_post} = .87$; $\omega_{knowledge_pre} = .80$, $\omega_{knowledge_post} = .87$).

Analysis

This study included quantitative and qualitative analyses. Quantitative analyses assessed changes in climate change knowledge and plausibility scores from pretest to posttest using paired sample t-tests. Qualitative analyses occurred in four waves: three waves after each of the three design iterations and the fourth after all data was collected. For each design iteration, recordings from interviews were transcribed and analyzed using NVivo. Interviewers wrote analytical memos based on an open analysis of each interview transcript. Conclusions that were derived from analyses were used to modify and improve the Estimation Game and to test emerging conjectures (Bakker, 2019; Cobb et al., 2003; Hoadley & Campos, 2022; Design-Based Research Collective, 2003) to address our central research questions. Throughout

this process, our team met weekly to discuss analyses, insights, and conclusions, and to plan and execute modifications to the Estimation Game design prior to the next iteration.

After three design iterations, all transcribed recordings were collectively revisited and open-coded by two independent coders for varying dimensions of student thinking (Corbin & Strauss, 2004; Saldaña, 2021). A codebook was collaboratively developed around themes that emerged. All themes centered around how students made sense of climate change numbers, with major categories being (a) quantitative reasoning strategies employed to estimate quantities (e.g., drawing from prior knowledge, mental computation, wildly guessing), and (b) emotions experienced while estimating climate change numbers (e.g., emotions about climate change vs about performance). Coders then independently coded all data over the course of four weeks and met during weekly meetings to calibrate and revise the codebook definitions as needed (Saldaña, 2021). During meetings, the lead author engaged coders in a consensus process where we discussed code occurrences until all members of the team agreed on the best representation of the data. The finalized codebook with definitions of all codes and subcodes with examples can be found in Appendix SD in the Supplemental Materials.

Findings

Survey Results

Survey results revealed evidence of growth from pretest to posttest (see Fig. 2). At pretest, students had an average knowledge score of M = 2.4 of 5 (SD = 0.50) and an average plausibility perception score of M = 4.87 of 6 (SD = 1.50). Half of the 12 students agreed that there was a scientific consensus on human-induced climate change on average, and 9 of 12 students initially indicated that they thought human-induced climate change was plausible on average. At posttest, students improved their average knowledge score to 2.91 of 5 (SD = 0.46), with only three students maintaining on average that there is no scientific consensus on climate change. This was a learning gain of about 0.62 standard deviations, and a paired sample t-test revealed that the change was statistically significant (p=.048, Cohen's d = 0.62). Plausibility scores also improved to M = 5.08 (SD = 1.28), with only one student maintaining that climate change does not seem plausible at the conclusion of the study. This is a gain of .09 standard deviations, though this change was not statistically significant (p=.715, d = 0.08).

[Figure 2 Here]

RQ1: Iterative Design of the Intervention

We conducted three iterative design cycles to refine the game-based climate change estimation intervention. The first iteration built on the original intervention developed by Authors (2024b), in which participants estimated 12 climate change values and received feedback including the true value, accuracy ratings (one to five gold stars), explanatory text, and source links. These features were grounded in theory suggesting that estimation activates prior knowledge, which can be restructured

through exposure to corrective information (Dole & Sinatra, 1998; Lombardi et al., 2016; Ranney et al., 2001).

Four enhancements were introduced prior to the first interview round to increase comprehension and affective engagement. First, we added a linear number line visualization to display estimates alongside true values. Second, we modified accuracy scoring to reflect order-of-magnitude error rather than absolute error to provide more lenient feedback and support engagement. Third, we incorporated game-like elements, including a themed progress bar, animated interface, and cumulative score. Fourth, we updated the visual design to include color and animation.

Feedback from the first interview round primarily resulted in text revisions and minor bug fixes. For example, several students expressed confusion about the term “CO2,” leading us to replace it with “carbon dioxide.” Students also reported skipping explanatory text because it was too lengthy, prompting a reduction in text length by approximately 50%.

The second round of interviews yielded additional refinements, including clarifying technical terminology (e.g., specifying greenhouse gases such as carbon dioxide), addressing minor usability issues, and improving readability. Following the final round of interviews, we implemented minor wording revisions and adjusted source links to open in new tabs to prevent loss of progress. The final intervention is shown in Fig. 3 (see link blinded for review).

[Figure 3]

RQ2: How Students Responded to the Intervention

Inductive coding of the full set of interview transcripts revealed two themes: (a) quantitative reasoning, and (b) emotions experienced while estimating climate change numbers. See Table 1 for a summary of the dimensions and interview excerpt examples. Also see the “Two Illustrative Cases” section for a comparison of two cases that illustrate these dimensions.

[Table 1]

Reasoning With Climate Change Quantities

When numerically estimating climate change quantities, students demonstrated a three central quantitative reasoning processes: they drew from their prior knowledge, used mental computation strategies, and wildly guessed. *Prior knowledge* had four subdimensions—when explaining their reasoning, students sometimes referred to information from their *educational experiences* (e.g., content they learned in class), *personal experiences* (e.g., an observation unrelated to academics), knowledge gained from a *prior item* within the study, or shared that they knew something, but *did not specify* where they learned it from (e.g., could not remember). Students also applied *mental computation strategies* when manipulating given numbers to better estimate unknown numbers, either by proportionally *extrapolating* trends over time, explicitly using *arithmetic operations*, or *not specifying* how they used the provided information. Evidence suggested that one student also explicitly used *digit rounding*

techniques. We also found that all students *wildly guessed* (e.g., reporting that they "have no idea" and thus make a random guess) at least once.

Students' Emotional Responses to New Information

We also found that students had various emotional responses when shown climate change values. Emotions were sometimes *in response to climate change information—relief* that climate change was not as severe as expected, *sadness* about the state of the world, or surprise at receiving novel information. Other times, emotions were *responses to students' own performance—excitement* about accurate estimates or *disappointment* in inaccurate estimates.

Two Illustrative Cases

In this section, we present two cases—Emma and Carlos (pseudonyms)—that illustrate the dimensions of quantitative reasoning strategies and emotional responses we identified. Emma identified as a Non-Hispanic White female in 9th grade, and Carlos a Hispanic White male in 9th grade. As with most students we interviewed, Emma and Carlos started with high levels of plausibility perceptions, endorsing the idea that climate change is happening and caused by humans (M_{Emma}=5.8, M_{Carlos}=5.0, maximum = 6), but both held misunderstandings about climate change (M_{Emma}=3.56, M_{Carlos}=3.8, maximum = 5). For example, in the pretest survey, Emma and Carlos agreed or strongly agreed that scientists think that "We cannot know about ancient climate change." Additionally, both drew from their prior educational knowledge to make sense of data and used mental computation strategies of: extrapolation, use of arithmetic in estimation, and occasionally guessed. However, in terms of the emotional responses to climate data, Emma showed more frequent *climate-related emotions*, while Carlos frequently demonstrated *performance-related emotions*, though both showed similar improvement at posttest, both in terms of plausibility (M_{Emma}=6, M_{Carlos}=5.5) and knowledge (M_{Emma}=4.3, M_{Carlos}=4.3).

Quantitative Reasoning

As noted, Emma and Carlos did not substantially differ in terms of the quantitative reasoning strategies they employed when estimating climate quantities, as we illustrate here.

Prior Educational Knowledge. Both Emma and Carlos drew on prior educational knowledge to derive their estimates. For instance, when asked to estimate how many billions of tons of carbon dioxide the U.S. releases each year (given carbon emissions in the European Union as a benchmark), both participants drew from their prior educational knowledge about industrialization. Emma stated: "I would say probably 2.8 because of how the US does produce a lot and does it major in the economy and there's a lot of people here. And some of the countries in the European Union are really tiny… but they are really tightly packed." Carlos reasoned similarly: "The USA is really industrialized everywhere. It's all factories, and there's like a lot of carbon dioxide being released, so I'd say 4 billion." Activation of prior knowledge while estimating quantities is considered a crucial component of this activity and is linked to deeper knowledge revision when students are later presented with the true value (Ranney et al., 2001).

Mental Computation. Carlos and Emma (along with all participating students) made use of mental computation processes when reasoning with given quantities ("hints") to better estimate the unknown quantities. Specifically, both employed *extrapolation*, *mental arithmetic*, and at times, *did not specify* the strategy employed when using given quantities. For example, when asked to estimate the average global temperature change over the last 50 years (given that temperature increased by 0.7 degrees Fahrenheit between 1900–1950), Carlos stated: "I would say 3 degrees, because if it's 0.7 [°F increase] and 50 years [from 1900–1950]; in the last 50 years, I'd say 2.5 [°F increase]. I don't think it would be more than that." Here we see Carlos extrapolating by coordinating the hint and target quantities, recognizing that both intervals represent 50 years and extending the given temperature change to estimate the change in degrees Fahrenheit over the target period. Emma used similar reasoning for the same item, but was less specific with her use of the given quantity,"I think somewhere around 2.3 [°F increase in the last 50 years]… 0.7 is very high and 2.3 is also very high."

Emma also explicitly applied mental arithmetic to given values. In the tutorial activity, Emma was asked to estimate the number of pennies that fit inside the tennis ball (given the hint: 53 pennies fit inside a ping pong ball). She estimated the size relationship between a tennis and ping pong ball: "a tennis ball is maybe three, maybe four times bigger than a ping pong ball… [and] 53 times 3 would be 159, right?" The application of mental computation strategies while estimating quantities was expected, as the design was intended to prompt learners to apply mathematical strategies to advance their gameplay, thereby imbuing these mathematical skills with new perceived utility (see, e.g., Authors, 2024a).

Wild Guessing. At times, Emma and Carlos transparently reported that they did not know where their estimate came from, that they had guessed. Emma's reasoning behind her estimate of sea level rise exemplifies guessing: "I'm going to say 24 [inches of sea level rise]… I don't know because I was guessing… I don't know why I came up with 24." Similarly, when estimating the percentage of scientists that agree that climate change is happening, Carlos stated: "I don't really pay attention to climate scientists… I'm not very sure. I'll just say two thirds." As illustrated, Emma and Carlos would occasionally report not knowing how to justify their estimates, despite their estimates being fairly reasonable, as was the case with most "wild guesses" throughout interviews. It could be the case that students' estimates of quantities were based on implicit (rather than explicit) plausibility judgments (see e.g., Lombardi et al., 2016).

Emotional Responses: Climate vs Performance Emotions

As noted, Emma and Carlos both improved similarly in terms of climate knowledge, plausibility, and in terms of the quantitative reasoning strategies they employed. What differed between them was the object of their emotional responses; both engaged emotionally with climate data, but Emma's emotions were more consistently directed toward climate implications, while Carlos's was more frequently focused on his estimation performance.

When estimating the number of countries (out of 195) across the world that had made commitments to curb climate emissions (revealed to be 175), Emma had underestimated the value to be 75 countries.

When provided with the true value, she responded: “What? [175 countries] is really good. I am very surprised and happy about it too. Huh. That is a nice surprise to know that I am very wrong.” Here she shares that she feels positive and hopeful about the result and about the prospect of global climate action, despite her inaccurate estimate. Later, in a separate item, after overestimating that 85 glaciers currently remain in Glacier National Park (compared to 150 glaciers in 1850), it was revealed that only 25 glaciers remain today. Here Emma expressed sadness: “Geez… well that’s sad.” Though Emma occasionally commented on her performance (“Wow. I was wrong. Well that happens.”) in most cases, Emma’s emotional expressions reflected stronger emotional investment in the environmental consequences of the results more so than her estimation accuracy.

In contrast, Carlos’s emotional responses more frequently centered on his estimation performance. When he correctly estimated that glacier volume in the European Alps decreased by approximately 50%, he responded: “Dude, I was right,” expressing satisfaction with accurate estimation rather than distress about glacier loss itself. Similarly, Carlos showed surprise at the magnitude of scientific consensus on climate change. When asked what percentage of climate scientists have stated that it is very likely that humans are responsible for the warming of the earth in the 1900s, Carlos initially estimated: “I don’t really pay attention to climate scientists, but I would say that, I’ll say two-thirds of ‘em.” Upon learning the actual percentage, he responded: “Oh shoot, 97.5… that was a lot more than I thought.” This reaction demonstrates surprise at the gap between his estimate and the scientifically accepted value. While Carlos did express being “glad that more countries are doing it than I thought” when learning about climate commitments, more often his emotional responses predominantly focused on estimation accuracy.

These two cases illustrate how students in our study different in terms of their emotional responses, despite using similar quantitative reasoning strategies and showing similar levels of learning gains. As consistent prior research with undergraduate students (Authors, 2024a, Ranney et al., 2016), students in our study tended to coordinate their relevant prior knowledge with their mental computations when estimating climate change numbers. Yet our finding that students also tended to have contrasting emotional responses when shown the true values (climate vs performance emotions) suggests that students can process the same climate change information through different emotional lenses. Namely, Emma’s emotions connected her to the real-world implications of climate change, while Carlos’s emotions kept him invested in the estimation task itself.

Discussion

We aimed to develop and assess student responses to a socioscientific data investigation activity geared towards channeling mathematical skills for a more environmentally sustainable future. Namely, we explored a game-based approach that positions mathematical reasoning skills as an in-game strategy to foster affective engagement with climate data and learning.

Over the course of three design iterations, we developed an online learning intervention for secondary students intended to tap into their prior knowledge to support their comprehension of novel climate change data, and assessed their affective responses in relation to their learning outcomes. Guided by principles inferred from the DLCC model, we developed this intervention with the assumption that, as students wrestle with the meaning of data, they consider or reconsider scientific explanations for the data, and potentially revise their knowledge and adopt new scientific ideas and explanations as a result. As such, the game-based interface we developed prompted students to estimate climate change numbers and compare their estimates to scientifically accepted values.

We found that students tended to draw from their prior educational and personal experiences and made use of mental computation strategies while estimating climate change quantities. Often, this coactivation was seamless, with students mentally rescaling given values at rates shaped by their prior knowledge about climate change. This interweaving of mathematics and prior knowledge while formulating an estimate is an important component of the learning experience; namely, when students are later presented with the true value, there is potential for knowledge revision in terms of both mathematical strategies and scientific explanations. Our findings are consistent with prior research with undergraduate students demonstrating that learners coordinate prior knowledge and mental computations while numerically estimating socioscientific numbers (Authors, 2024; Ranney & Clark, 2016). Our findings provide evidence that secondary students also engage in these coordination processes, and suggest that numerical estimation activities may be a useful strategy for teachers intending to support students in interweaving mathematical and socio-scientific reasoning.

Another contribution of this work lies in highlighting the role of emotion in students' engagement with climate change data. During cognitive interviews, we observed that students' affective responses were not incidental to learning, but instead intertwined with how students interpreted quantitative information, evaluated their own reasoning, and made sense of climate change as a scientific and societal issue. This is consistent with the DLCC's assertion that affect and emotion are core components driving conceptual change (Authors et al., 2025b; Lombardi et al., 2016). Importantly, students' emotional responses appeared to cluster into two related but distinct categories: emotions tied to climate change itself (e.g., sadness, surprise, and hope) and emotions tied to performance (e.g., excitement, disappointment). Distinguishing between these "climate emotions" and "performance emotions" helps us see that students can navigate the emotional space of learning about climate change through multiple pathways. Indeed, in our focal cases of Emma and Carlos, as with many students in our study, we found that both students revised their beliefs and understanding about the scientific consensus on climate change, but while Emma did so primarily processing her emotions related to the demonstrated impacts of climate change, Carlos was more emotionally invested in his performance.

These findings suggest that either emotional response seems to facilitate learning, but in different ways. Performance-related emotions seem to support engagement and persistence by framing estimation as an achievable challenge, while climate-related emotions may orient students toward the broader implications of the data—both of which can enhance student learning. And though emotionally

processing the devastation to the planet is an important stage in investment in environmental concern and action (Wray, 2023), we caution readers that overly intense affective reactions—particularly when centered on climate severity—can risk overwhelming students or narrowing their focus (Stoknes, 2015), pointing to the need for careful instructional design. Future research might examine whether different emotional profiles might be related to a wider variety of outcomes, such as climate anxiety/hope, willingness to act, and climate behaviors. Further, future research might investigate whether certain combinations of estimation strategies and emotional responses (performance-oriented, climate-oriented, both, or neither) are conducive to conceptual change and/or sustained engagement.

The game-based structure of the Estimation Game seems to have played a key role in shaping these emotional dynamics. Design features such as immediate feedback, supportive text explanations, and action-oriented messaging were intentionally included to maintain a constructive emotional tone. Rather than emphasizing failure or deficit, the performance component reframed numerical estimation as sense-making under uncertainty, potentially mitigating climate anxiety and disengagement. This aligns with perspectives from critical mathematics education that position sustainability-focused learning as an opportunity for students to “read and write the world” through mathematics in ways that are empowering rather than paralyzing (Weiland, 2017; Rasmussen, 2010). By pairing challenging climate data with messages that emphasize agency and future-oriented action, the intervention sought to create positive and meaningful learning experiences around climate change.

Limitations

This study had necessary limitations. This design-based study prioritized iterative refinement and rich student responses rather than causal inference, and as such, the relatively small sample limits generalizability. Additionally, the predominantly Hispanic student population—while often considered a strength in addressing understudied groups—may not reflect all secondary contexts. Further, students in our sample generally had high rates of climate change acceptance—and while this is proportional with the national average in the U.S. in this age group (e.g., Worth, 2021), not all teaching contexts have students with such high levels of climate acceptance. Future work should employ experimental or mixed-methods approaches to examine causal pathways linking estimation strategies, emotional responses, and learning outcomes, and explore how this intervention functions across diverse educational settings.

Implications & Conclusions

This study contributes to mathematics education for sustainable futures. First, it highlights how reasoning with data within game-based contexts can strengthen both mathematical understanding and climate change awareness. Second, it foregrounds emotion as an integral component of data-driven learning, suggesting that affective engagement may be necessary for sustaining attention to issues of sustainability. Third, findings demonstrate how design features can be refined to connect quantitative reasoning, emotion, and sustainability-oriented mathematics learning. Collectively, these insights position mathematics education as a vital tool for interpreting quantitative evidence and considering the scientific consensus on climate change. We believe that empowering students with mathematical tools

for reading and writing their world can advance the pursuit of creating a more environmentally sustainable future.

Declarations

Ethics Approval

We have registered this study with the [*institution blinded*] Institutional Review Board [*IRB identifier blinded*].

Consent

Informed consent was obtained from all participants.

Data Availability

The data that support the findings of this study are not publicly available due to restrictions related to participant confidentiality and institutional review board protocols. Study materials, including instructional resources and measurement instruments, are provided in the supplementary materials.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

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Authors' Contributions

[A1 blinded] Conceptualization, Methodology, Supervision, Project administration, Funding acquisition, Investigation, Writing - Original Draft, Writing - Review & Editing; *[A2 Blinded]* Investigation, Writing - Original Draft, Writing - Review & Editing, Data Curation.

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Footnotes

1. Note that this study reports on the first phase of a two-part project. The first phase reports the development of the Estimation Game. The second phase tested the effectiveness of the intervention in an experimental research design (i.e., see Authors, 2024a).

Tables

Table 1.

Coding Guide for Interview Data

THEME 1. QUANTITATIVE REASONING	
Quantitative Reasoning Processes When Estimating Climate Change Quantities Strategies and reactions involved when estimating and interpreting climate change quantities. (i.e., how people make sense of climate change numbers).	
Wild Guess	
	Evidence of wild guessing. Seems to be "pulling a number out of nowhere" without much consideration or justification for where the number came from. No context whatsoever given for the estimate. E.g., "I was just typing in numbers," "I made a wild guess."
Mental Computation Strategies	
Unspecified estimation strategy	Evidence that the individual used the given benchmark values without specifying what they specifically did with the benchmarks (e.g., "I used the hints," "I used the given information")
Extrapolation (proportional reasoning)	Evidence that the individual used the given benchmark information and beliefs about projected trends to estimate the unknown quantities, though the mathematical procedure may not always be clear. (e.g., they notice a "trend," that the "numbers increase/decrease between time periods" using rate-based reasoning and time-interval matching)
Arithmetic (+ − × ÷)	Evidence that the individual is explicitly using arithmetic. This could be repeating a given number over and over to estimate an unknown number, or explicitly multiplying, dividing, rescaling a number to obtain their estimate (e.g., "The hint says two more after one year. So that's another two and another two and and another two. Two times three.")
Flexible Rounding	Evidence that the individual has rounded a number to make mental computation easier (e.g., "4.3 is close to 4, and roughly triple that makes 12").
Drawing from Prior Knowledge	
Educational Experiences	The individual references information from their prior learning experiences to estimate or make sense of unknown quantities (e.g., "I learned about this in geology class in middle school…" "I saw a documentary [in a science class] once that said that methane has basically doubled in the last 50 years… so I'll double this number").
Personal experiences	The individual references information from their personal experiences to estimate or make sense of unknown quantities (e.g., "It has been getting smoggier in [my area] recently, so I think that CO2 has increased...", "it has been hotter recently…")
Prior Item	Evidence that the individual used information from a previous item in the game to estimate the given number. (e.g., "I remember in the question before it said that ice melt increased 40% so my guess here is the same…")
Unspecified Reasoning	Evidence that the participant shares their reasoning and perspectives on the matter, but don't specify where they learned it from. E.g., "I know that polar bears are dying so I think ice has decreased…," "...most people think climate change is a big deal and they probably have a good heart…," "I made an educated guess"

THEME 2: EMOTIONAL RESPONSES TO CLIMATE CHANGE NUMBERS	
Emotional Reactions to Accuracy Feedback The kinds of affective/cognitive/motivational reactions people demonstrate when shown the scientifically accepted climate change value after estimation.	
Emotions About Climate Change	
Hope / Relief	Evidence that the individual feels relief that the climate change quantity was not as severe as they expected, and hopeful regarding the future of the world in relation to the climate change evidence provided. E.g., “I'm glad that more countries are [committing to climate action] than I thought.”
Sadness	Evidence that the individual feels sad and perhaps hopeless about the future of the world in relation to climate change evidence.“Geez [glaciers are melting], well that's sad.”
Surprise	Evidence that the individual is surprised at information about the scientific consensus or impacts of climate change. that their estimate was incorrect “I am very surprised and happy about it too. Huh. That is a nice surprise to know that I am very wrong.” “97.5%! Wow. So not a lot of scientists deny it.”
Emotions About Performance	
Excitement	Evidence that the individual feels excited regarding the accuracy of their estimate. “Amazing job. I was so close. *claps* Look at that. It was 151%. Yay, I got five stars!” “Woo, 5 stars!”
Disappointment	Evidence that the individual feels disappointed regarding the inaccuracy of their estimate. “Seriously? 5 billion times, I got one star. That's my lowest score. That's really sad. Wow.”

Table 2.

Summary of Themes Related to Student Reactions to the Estimation Game (N = 12)

Dimension	Sub-Dimension	Students who used this strategy	Example Excerpts from Student Interviews
Theme 1: Quantitative Reasoning Demonstrated While Estimating Climate Change Quantities			
Prior Knowledge	Educational	10	● I was in geography and I saw a picture from 2009 to 2020, and it raised by a lot, so I'll say, say 65 inch increase.
	Personal	7	● It's really cold right now [in my location]...so [I'll estimate] maybe like 7 increase
	Prior item	6	● I'm going to use the same answer that I used in my first question.
	Unspecified Reasoning	11	● I remember hearing somewhere, I don't know if I was researching, but it was something, I want to say 30. ● [how many scientists agree?]...most people think climate change is a big deal and they probably have a good heart… ● I know that polar bears are dying so I think ice has decreased…
Mental Computation	Extrapolation of given value	10	● [Reading hint] Global sea levels rose by 1 inch between [1900 and 1920] that's not a lot…. But [now] it's more than that so it's honestly like 5 or 6.
	Arithmetic applied to given value	9	● Let's see, that was 28 years before this… soooo ice thickness in meters. I would just say 12. I'm just going to multiply by four.
	Unspecified use of given value	4	● I think it's gone down [compared to what was given in the hint]
	Flexible Rounding	1	● So we'll round the 53 to 50… and four times 50 is 200…
Wild Guess	Wild Guess	12	● I'd say four. Wild guess ● I'm not familiar with this, I'm just going to have to guess
Theme 2: Emotional Response to New Information			
Emotions (about climate change)	Hope / Relief	5	● I'm glad that more countries are [committing to climate action] than I thought.

	Sadness	8	• Geez [glaciers are melting], well that's sad.
	Surprise	8	• I am very surprised and happy about it too. Huh. That is a nice surprise to know that I am very wrong. • 97.5%! Wow. So not a lot of scientists deny it.
Emotions (about performance)	Excitement	6	• Amazing job. I was so close. *claps* Look at that. It was 151%. Yay, I got five stars! • Woo, 5 stars!
	Disappointment	5	• Seriously? 5 billion times, I got one star. That's my lowest score. That's really sad. Wow.

Figures

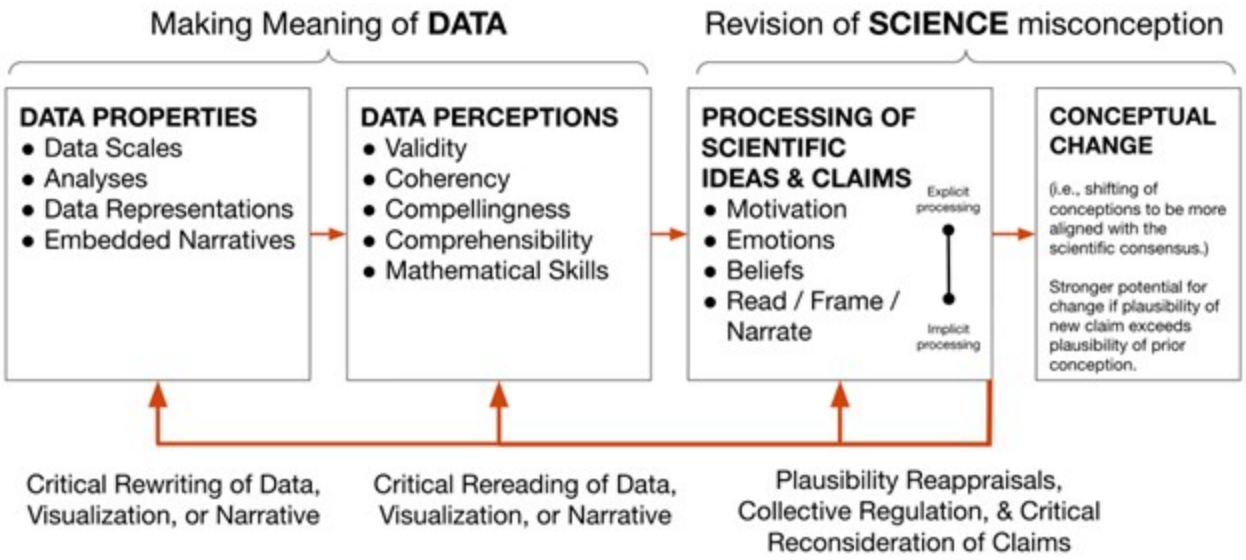
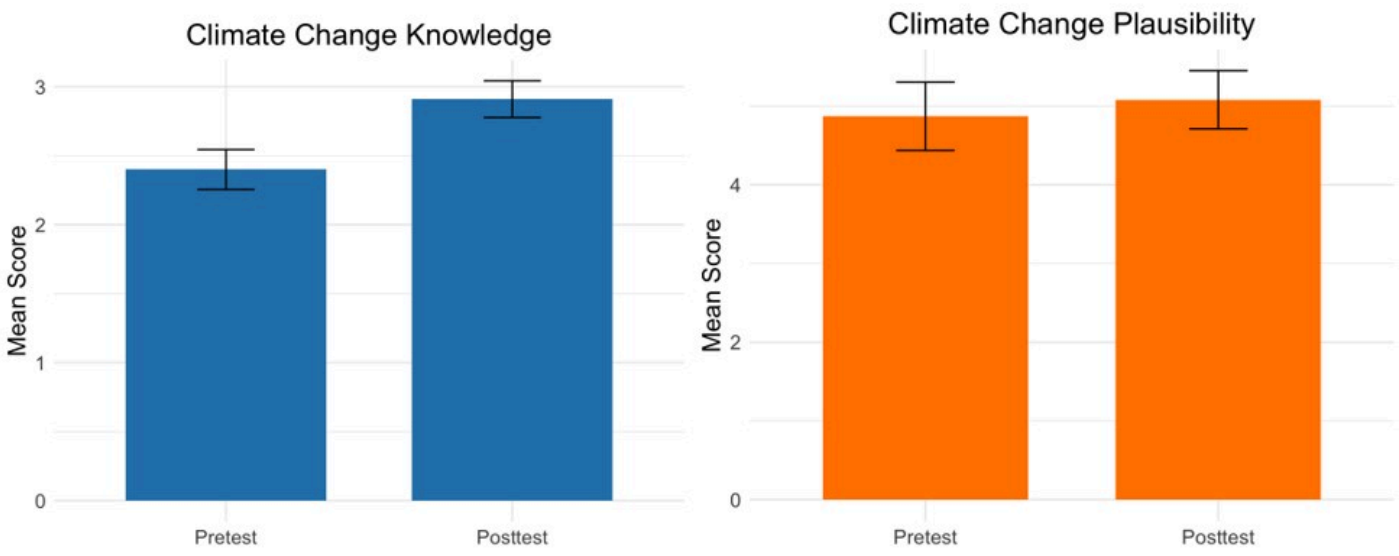


Figure 1

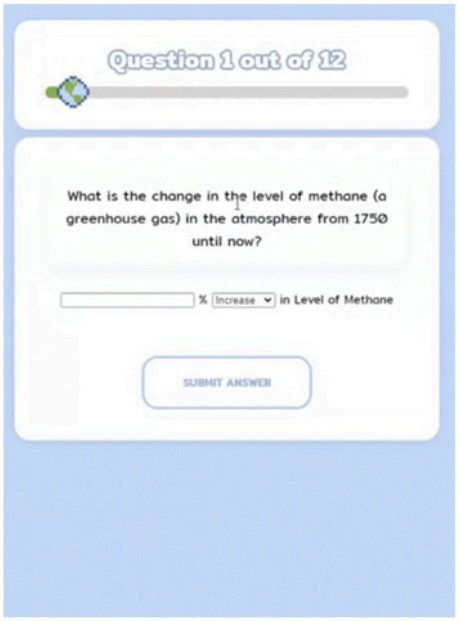
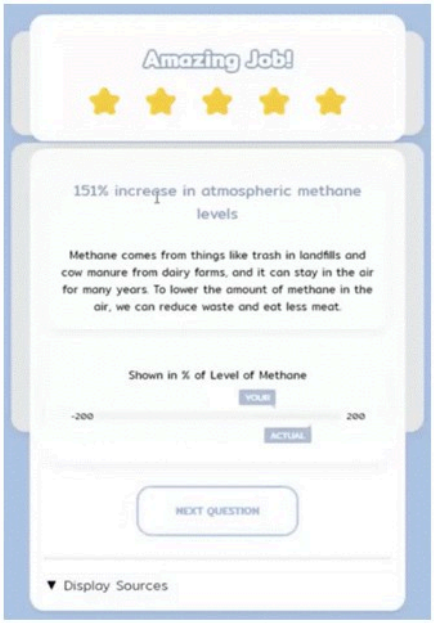
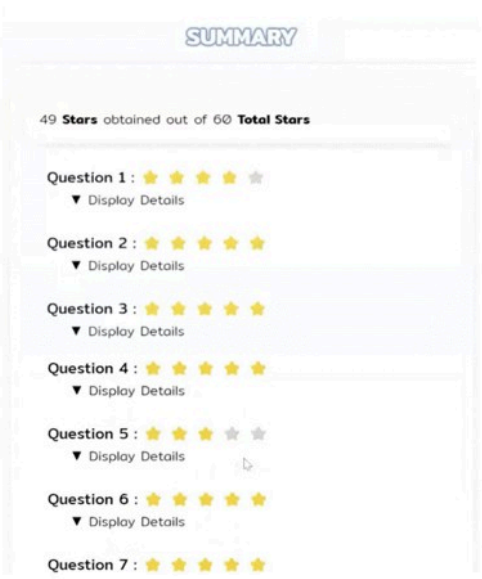
An Illustration of the integrated Data Literacy for Conceptual Change (DLCC) Model



Note. Intervals represent ±1 Standard Error above and below the mean.

Figure 2

Mean Change in Climate Change Knowledge and Plausibility Perceptions (n = 12)

Students are prompted to estimate a climate change number	True value pops up with accuracy feedback & number line & sources	Summary screen after Estimating 12 Quantities
		

Note. Videos describing this web-app as well as a revised, usable version can be accessed via [*Link blinded for peer review*].

Figure 3

Screenshots of the Estimation Game Developed for this Study.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- ESMSupplementalMaterials.docx