Dirt Don't Hurt: How Relevant Soil Data Can Support Learning and Motivation at a Hispanic Serving Institution

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Abstract. (133 words)

To create opportunities for meaningful applications of data-science for diverse students, we developed and implemented an online learning module focused on engaging students at a Hispanic Serving Institution (HSI) in an analysis of authentic soil data. Development of the module occurred over three design iterations involving interviews with 10 undergraduate STEM students. We then implemented the finalized module in three undergraduate microbiology classrooms (*N* = 118) using a pretest, posttest, comparison group quasi-experimental study design to assess whether the module improved student microbiology knowledge, perceived relevance of data science, and motivation. Findings revealed that, after adjusting for key variables, the intervention group demonstrated significantly greater microbiology knowledge than the comparison group. Path analyses revealed indirect effects of the intervention through value and interest in STEM. We discuss how findings contribute to theory and practice.

Keywords: biology education, conceptual change, data literacy, microbiology education, quasi-experimental research

Dirt Don't Hurt: How Relevant Soil Data Can Support Learning and Motivation at a Hispanic Serving Institution

In today's world, data is ubiquitous, and its impact is felt across a wide range of industries. With the increasing amount of data available, the ability to analyze, interpret, and draw insights from data and data visualizations is becoming a necessary skill for many careers, likened to the importance of reading and mathematical literacy (Börner et al., 2019). Despite the current high demand for data science education, traditional courses offered by statistics and computer science departments are not meeting the needs of those seeking training (Baumer, 2015), and there is a lack of diversity with regards to race and gender in science, technology, engineering, and mathematics (STEM) attainment (National Science Foundation, 2015). Hispanic students, in particular, are underrepresented in STEM fields, particularly in data science (Fry et al., 2021).

Hispanic students have rich funds of familial, community, and cultural knowledge, such as systems thinking, empathic reasoning, and knowledge of production, that can be leveraged for STEM learning but seldom are (Cruz et al., 2018; Gonzalez et al., 1995; Wilson-Lopez et al., 2016). A central goal of this project was to create interdisciplinary learning environments that leverage these cultural resources to enhance Hispanic students' STEM learning and motivation. Namely, for the current project, we created an online module addressing topics in soil microbiology that uses data science tools to help students make meaning of authentic and relevant soil data. We intended to create personally relevant learning contexts for students taking a microbiology course at a Hispanic Serving Institution (HSI) to engage with and draw conclusions from visualizations of authentic soil data and assess their impacts on STEM learning, persistence, and engagement. We argue that personally relevant data experiences can support student motivation and learning around these topics.

Theoretical Framework

To frame how relevant data visualizations can support science learning for Hispanic students, we integrate theories of Conceptual Change, Data Visualization Literacy, and Expectancy Value.

Conceptual Change

Conceptual change theory posits that presenting people with novel information can shift their conceptions about science topics to be more aligned with the scientific consensus (Dole & Sinatra, 1998). For example, the Plausibility Judgments for Conceptual Change model (PJCC; Lombardi et al., 2016) posits that when people are presented with novel information (such as novel microbiology data), they initially process the information, judge the plausibility of claims supported by the information, and then potentially restructure knowledge and change their misconceptions as a result. When initially processing information, novel data must be *comprehensible* (depending partly on learners' skills to interpret the information), *coherent* with their prior experiences, *compelling* and relevant, and perceived as *valid* (e.g., information stems from a credible source) for conceptual change to occur (Dole & Sinatra, 1998; Lombardi et al., 2016). After people process novel information, they then judge the *plausibility* of the claims associated with this information. Plausibility judgments can be either implicit or explicit, with more explicit processing depending on the individuals' beliefs about knowledge, motivation, engagement, and emotion and ultimately predicting the likelihood that conceptual change will occur.

This conceptual change model thus suggests that, to support student understanding around concepts in microbiology and data science, it is necessary to engage them with relevant, comprehensible information that fosters motivation, engagement, and positive emotion. Some existing research supports the idea that undergraduate biology students shift their conceptions as a result of wrestling with novel information (Tanner & Allen, 2005), though much of the literature is correlational, does not explore the role of motivation or emotion, and does not assess the role of relevant data in learning. Other studies have used experimental methods to show that motivation, emotion, and data literacy play key roles in the conceptual change that occurs when learning from relevant scientific data (Thacker & Sinatra, 2022; Thacker, 2023, 2024); yet do not explore whether these conceptual change processes are important specifically for microbiology learning. Our study attempts to address these gaps by developing and testing an intervention that intends to promote scientific understanding by engaging students in making sense of real soil data. Specifically, we aimed to enhance two specific properties of information presented to students that are indirectly linked to conceptual change: we aimed to make information *compelling* by promoting utility value and *comprehensible* by promoting data visualization literacy.

Data Visualization Literacy

Advances in the study of visualizations for STEM learning suggest that imagery has potential for helping students comprehend information by grounding abstract concepts in perceptions of scientific representations (Schwartz & Hiezer, 2006). There are a number of properties of data visualizations that are related to their efficacy for learning and communicating science content. For example, according to the Data Visualization Literacy Framework (DVL-FW), different types of visualizations can be designed to fulfill information needs of the learner, and each visualization type requires specific skills for interpreting them (Börner et al., 2019). According to this framework, a central process required to interpret data from visualizations is *translating* relevant problems of interest into problems of data. That is, before acquiring, analyzing, and visualizing data, individuals must first understand how the data relates to a relevant situation. As such, to improve students' interpretation of data visualizations, they may need support in translating real-world situations and problems into data. A goal of this project was therefore to leverage students' prior knowledge and experiences to contextualize data, data analysis, and data visualizations. In other words, we focused on improving student data literacy as a means to promote the *comprehensibility* of soil data, thus its personal relevance, plausibility, and ultimately microbiology learning (Lombardi et al., 2016).

Yet, while the DVL-FW is useful for framing the importance of data literacy, to date, few data visualization literacy studies investigate how underrepresented groups might apply data visualization literacy skills in microbiology settings. In this study, we developed and tested an intervention to promote microbiology knowledge among underrepresented groups by supporting their data literacy and motivation to learn.

Expectancy Value Theory

As noted, compelling information that promotes motivation is key to fueling learning, conceptual change, and successful academic performance (e.g., Dole & Sinatra, 1998; Gottfried et al., 2013; Vu et al., 2022; Lombardi et al., 2016). Expectancy-Value Theory (EVT) posits that academic motivation is promoted by learners' *expectancy* (expectations for success) and *task value* (perceived value imbued on the task at hand; Eccles et al., 1983; Wigfield et al., 2017). According to EVT, there are four different types of task value: *intrinsic value* is when a learner values a task because they find the activity enjoyable for its own sake, *attainment value* is perceived personal importance of a task as it relates to one's identity, *utility value* refers to perceptions that a task may be useful to a learner to achieve their present or future goals, and *cost* is the extent of time and effort that is perceived to complete a task. Interventions can be designed to promote these different forms of task value; we drew from those that promote utility value.

Drawing from EVT, several researchers have created classroom interventions to promote utility value and learning by supporting students in making connections between their lives and the content they are learning (Eccles et al., 1983; Hulleman & Harackiewicz, 2021). For example, students across disciplines often wonder "Why are we learning this?" and addressing this question with information about why content is useful in students' lives can promote utility value (Eccles et al., 1983; Wigfield et al., 2017). Namely, when interventions are personal, specific, and emphasize how content can be relevant to students' lives, utility value interventions can significantly increase student learning and interest (Hulleman et al., 2018) and may be particularly effective for underrepresented students in higher education (e.g., Harackiewicz et al., 2016).

To explain how utility value intervention elements might be linked to learning and interest outcomes, Hulleman and Harackiewicz (2021) proposed a logic model grounded in EVT positing that interventions might trigger a cascade of psychological *processes* which leverage psychological and behavioral *mechanisms* through which such interventions influence academic *outcomes*. Indeed, in a review of the empirical literature, Hulleman and Harackiewicz (2021) argue that utility value interventions designed to promote perceived personal relevance of content initially trigger three psychological processes: perceived utility value, increased expectancies for success, and lowered perceived cost. These psychological processes then trigger psychological and behavioral mechanisms. Psychological mechanisms, of *identification* with the activity, greater *affective engagement* (e.g., excitement related to learning), and *interest* in the topic, as well as behavioral mechanisms of *behavioral engagement*[1] (e.g., time spent on task), and heightened *performance* (on formative assessments, such as class assignments and quizzes), are both linked to achievement outcomes such as grades, persistence, with particularly strong effects for marginalized groups and low achieving students.

A patchwork of evidence supports various subsets of relationships articulated in the utility value intervention process model. Experimental evidence suggests that helping undergraduate students see how content is relevant to their lives can promote positive motivational and academic outcomes (e.g., STEM interest, utility value, grades, test scores, and passing rates), with stronger effects for marginalized groups of students in STEM (Hulleman et al., 2010; 2017; Harackiewicz et al., 2016; Rosenzweig et al., 2019; Kossovich et al., 2019; Seyranian et al., 2023). Yet, despite the Utility Value Intervention Logic Model's predictions of indirect relationships between interventions, processes, mechanisms, and academic outcomes, few, if any empirical studies have synthesized these constructs and tested the indirect effects predicted by this model, especially in a microbiology or data science setting. As such, in this study we explored whether designing an intervention that emphasizes the relevance of microbiology and data science may indirectly promote learning through interest and engagement.

Summary

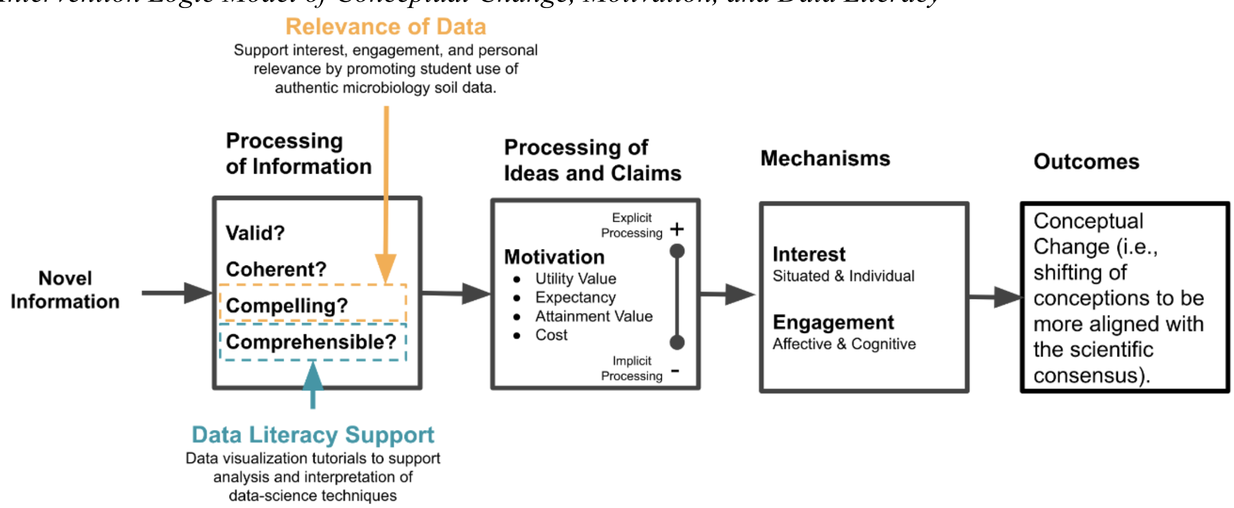
Synthesizing across Expectancy Value Theory, Conceptual Change Theory, and the Data Visualization Literacy Framework, we created an intervention logic model (Figure 1) that

[1] We should note that the psychological/behavioral mechanisms of engagement and interest are considered to be multidimensional constructs. Engagement is regarded in the literature as having behavioral, emotional, and cognitive dimensions (Fredricks et al., 2004). Behavioral engagement includes actions such as attendance, time on task, and participation. Positive emotional (or affective) engagement is characterized by experiencing joy or excitement, which Hulleman et al. (2021) refer to as "involvement." Cognitive engagement is the willingness to engage in effortful tasks, purposiveness, strategy use, and self-regulation. Similarly, the educational psychology literature distinguishes between situated interest, a state-based interest that is triggered by features of the environment to grab one's attention (e.g., a colorful magazine cover) and individual interest, a stable and trait-based interest in a topic (e.g., a personal, lifelong interest in mathematics; Schiefele, 2009).

informed our intervention development and that we also tested using path model analyses. Specifically, the model predicts that an intervention intended to expose students to compelling and comprehensible microbiology data that relates to students' lives would trigger motivational processes (i.e., improve utility value, expectancy, attainment value, and reduced cost). We posited that these process variables, in turn, would activate mechanism variables (student interest and engagement), which would predict increased learning outcomes (i.e., microbiology knowledge). Furthermore, we also sought to facilitate these processes by centering learning around compelling topics that students found relevant, and supporting data literacy to improve comprehensibility of the information.

Figure 1.

Intervention Logic Model of Conceptual Change, Motivation, and Data Literacy



Note: This intervention logic model synthesizes ideas across Conceptual Change Theory (Dole & Sinatra, 1998; Lombardi et al., 2016), Expectancy Value Theory (Eccles et al., 1983; Hulleman & Harackiewicz, 2021), and the Data Visualization Literacy Framework (Börner et al., 2019).

Current Study

To test this theoretical model, we designed and tested an interdisciplinary learning experience for undergraduate students at an HSI. We addressed the following research questions:

- **Research Question 1 (RQ1).** How can a learning intervention be developed to leverage undergraduate students' motivation for the learning of soil microbiology?

- **Research Question 2 (RQ2).** To what extent will such an intervention support students' microbiology knowledge, perceived relevance of data science, engagement, interest, and task value in STEM?
- **Research Question 3 (RQ3).** Will the hypothesized relationships between task value processes and achievement outcomes be mediated by mechanisms of interest and engagement? (See Figure 1)

This project addressed these research questions through a two-phase student-centered design and evaluation processes with both formative and comparative studies. Phase I of the project was a formative study focused on creating an online module for supporting underrepresented students' STEM learning and integrating crucial data science and microbiology skills, while also validating survey measures that assessed student learning and motivation outcomes. Phase II of this project was a comparative study testing the effectiveness of this intervention using a quasi-experimental research design and explored relationships between motivational and conceptual change variables.

Study 1: A Design-Based Research Study

Methods

To answer the first research question, we used a design-based research (DBR) approach to guide the development and revision of an interactive online intervention (Hoadley & Campos, 2022) focused on the topic of soil microbiology. As is characteristic of DBR (Anderson & Shattuck, 2012), the re-design, implementation, and revisions of the intervention occurred over several iterations and resulted in an open-source module geared for undergraduate students in a microbiology course, and can be easily shared with practitioners and the general public online.

We initially developed the module in SoftChalk Cloud as to create an open-access module that introduces undergraduate students taking a microbiology course to the Tiny Earth Initiative (Hurley et al., 2021). Tiny Earth is a national initiative concentrated on identifying new antibiotics in soil by encouraging undergraduate students to collect soil from the place where they live, study the bacteria in that soil, add their data to an online repository, and then analyze that data to potentially discover new antibiotic structures. At the time of this study, no local soil data had been uploaded to the Tiny Earth repository, so we focused the data analysis on existing data from other locations across the USA. In addition to introducing students to the goals and public data repository of Tiny Earth, the module introduced students to relevant information related to the antibiotic resistance crisis (the problem of diminishing effects of common antibiotics to stop bacterial infection), discussed microbial ecology factors that are important for creating soil conditions that harbor new antibiotics, prompted students to generate personally relevant research questions, provided a short tutorial on data visualization tools, and immersed students in soil data visualization interpretation.

Data & Analysis

Over the course of three design iterations, we conducted 10 recorded cognitive interviews (Desimone & Le Floch, 2004) via Zoom with a convenience sample of undergraduate students at an HSI participating in microbiology courses formerly taught by the third author in Summer and Fall of 2023. Students self-identified as Female (70%), Male (20%), Nonbinary (10%), Hispanic (50%), White (40%), Black (10%), Asian (20%), and English Learners (30%). Interviews were conducted virtually outside of the scheduled course meeting time and concentrated on eliciting student feedback to guide the revision of the module and pre-test, post-test survey instruments. Interviews were conducted by the first author and two graduate student assistants, none of whom were associated with any of the microbiology courses or familiar with any of the students interviewed. As is characteristic of cognitive interviews, the interview protocol centered on prompting students to "think aloud" as they completed the survey items and learning intervention. Upon completion of the intervention, before beginning the posttest, interviewers asked all participants to respond to an additional five questions concerning their opinion of the intervention, such as "What did you think [about the lesson]?", "Did you hit any bugs?", and "What would you change to make the lesson more engaging, relevant, or fun?". For the full interview protocol, see the Supplemental Materials, Appendix A.

Upon each iteration of pilot interviews, Zoom recordings were transcribed and open-coded for varying dimensions of student thinking (Corbin & Strauss, 1990) with special attention to examining student engagement, perceived relevance of the content, and learning around soil microbiology and data visualization literacy. Informed by these analyses, various aspects of the surveys and online module were revised to improve interpretability, perceived relevance, accessibility, usability, and effectiveness before undergoing subsequent iterations of interviews, and ultimately used in the Phase II study. Further, this phase provided cognitive interview data on our survey instruments, which we revised each iteration to ensure that students interpreted the items as intended to improve validity prior to Phase II.

At the conclusion of the three design iterations, the first author and a graduate research assistant then systematically coded all interviews again, concentrating on the final portion of the interview regarding learners' opinion of the intervention. This involved conducting another round of open coding, discussing similarities and differences in emergent codes and themes, creating a codebook that represented all codes (see Supplemental Materials, Appendix Y), systematically recoding all ten interviews using the codebook, and meeting weekly to arrive at a consensus on instances of each code. We summarize these findings in the next section.

RQ1 Results: A Module for Soil Microbiology Data Exploration

Results revealed that, after completing the intervention, many students shared both positive and negative feedback about their experience in regards to the lesson content. Our analysis revealed that this feedback was essentially targeted on the text, videos, images, relevance of the content, technical issues with the platform, and data science-specific comments. A summary of the codes, their frequencies, and examples that emerged from the interviews is presented in Table 1 and are defined in more detail in Appendix B in the Supplemental Materials.

Table 1.

Frequency of Codes Among Undergraduate Students Interviewed in Study 1 (N = 10).

Code	# of students	% of students	# of times coded	% of time this code was used	Example
Text - recommendations to break up text	3	30%	3	3.2%	● I feel like if this is bolded… [it would] break it up a little…
Text - negative remarks	8	80%	14	15.1%	● ...there are so many like paragraphs. I had to like scroll back and like, look for things.
Text - positive remarks	4	40%	4	4.3%	● Overall like [the text] was easy to follow, easy to understand.
Text - remarks that vocab is difficult	9	90%	15	16.1%	● ...[please change] any words that… a regular person wouldn't know.
Data Science negative remarks	5	50%	11	11.8%	● I would probably say that the data science part confused me a little bit…
Data Science positive remarks	4	40%	4	4.3%	● The most interesting was the antibiotic [data visualization]. Because… I wanna know more about… what's causing, like so many people to die...
Images - positive remarks	4	40%	4	4.3%	● I feel like… the charts, the maps, and everything, it does help like with answering some of the questions…
Images - preferred more/different images	5	40%	6	6.5%	● I would maybe add more pictures…
Relevance -	3	30%	6	6.5%	● There's literally not even any [data

recommendations to make content more relevant					representing the state I live in]. So like I don't know. Maybe it would be more interesting.
Relevance - positive remarks	3	30%	3	3.2%	● I'm a public health major, but I'm going for nursing. So I feel like these courses will benefit me because it's something that I need to know about for my future.
Videos - positive remarks	3	30%	3	3.2%	● There's videos. I think those help cause you get like, a more visual … [that] engages you more.
Videos - recommendations for more videos	6	50%	6	6.5%	● Maybe [add] a couple more videos. Just a couple.
Technological issues - identified	4	40%	5	5.4%	● [Researcher: Did you encounter any bugs?] Well, I mean other than the fact that I clicked the link and it didn't work.
Technological issues - did not identify	8	80%	9	9.7%	● [Researcher: Did you encounter any bugs?] Student: No, everything seemed, no other problems. I like that.

Generally speaking, results revealed that students' biggest issues with the module was in regards to the amount of challenging text they were required to read. For example, 8 of the 10 students had negative feedback about the text (e.g., "too much text") and 9 of 10 students mentioned challenges understanding vocabulary. While the most elements of the module perceived most positively by students was regarding the images and videos (i.e., 40% of students said they liked images and 30% said they liked the videos), though students also had recommendations that they would have liked to see *more* visuals (40%) and videos (50%). Very few students encountered technical issues (80% said there were "no bugs") though a few students still mentioned potential improvements (40%). Lastly, students seemed to have mixed feelings about the data-science content, with some indicating that they found the content confusing (50%) while others having positive things to say (40%).

These findings were critical for directing our attention to ongoing revisions to the intervention. Revisions to the intervention occurred after each design iteration, were based on the interview data, and concentrated on adapting survey instruments so items were interpreted as intended and revising the module to be more interactive, visually appealing, relevant, engaging for students, and improving ease of data and text interpretation. First, the most prominent set of revisions made across all design iterations was in regards to modifying intervention text to improve comprehensibility. Namely, across all three design iterations, we revised text by: reducing the amount of overall text, linking challenging vocabulary to glossary terms that pop-up when hovered, simplifying the language of unnecessarily complicated text, and organizing text into more "digestible" chunks, with particular attention to supporting English learners. Secondly, we responded to student recommendations by incorporating additional images, infographics, and data visualizations that revealed relevant insights about the soil data. A third set of revisions were in regards to promoting utility value and perceived relevance of the module. Three shared that they found the health-related aspects of soil microbiology to be most relevant for their lives and careers, which we kept in mind and emphasized when revising text and images. Fourth, across the three iterations, we incorporated additional interactive elements into the module such as quiz-like "checks for understanding" and two asynchronous discussion prompts using Padlet. The finalized intervention and survey instruments were used in the second phase of this project and can be accessed using this link [blinded for peer review].

Study 2: A Quasi-Experimental Study Testing Effects of the Design

Methods

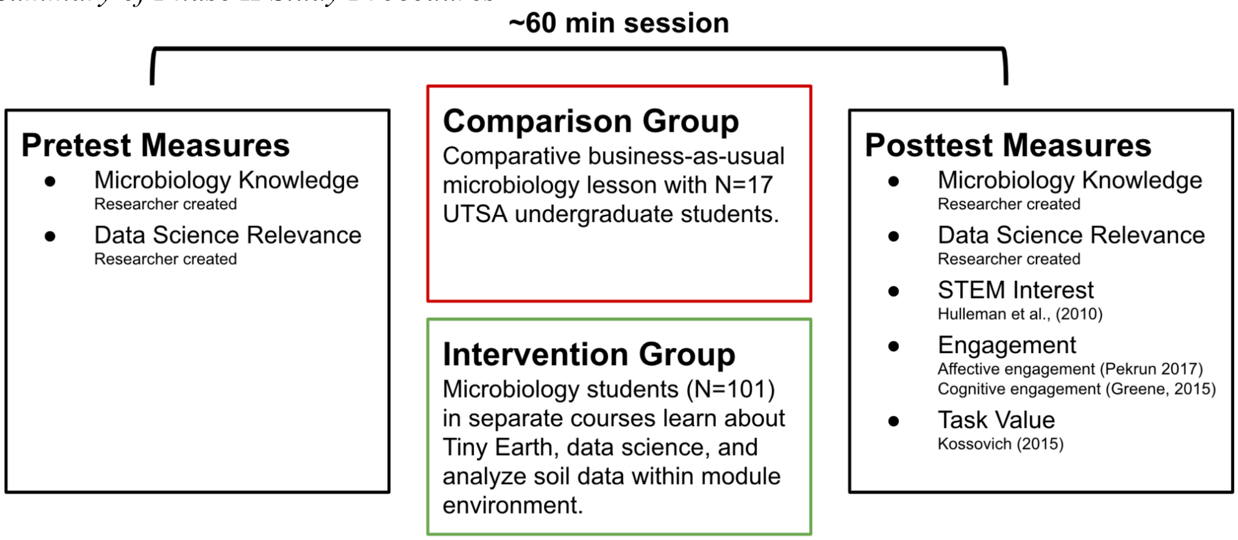
To answer the second research question, we recruited N = 118 undergraduate students from an HSI in a southern state of the USA. The intended sample size (100) was based on a rounded estimate from an a priori power analysis using G*Power which found the sample size required to detect an effect size of 0.15 for an equal samples F test with five predictors, power of .90, and alpha level of .05 (Faul et al., 2009). Students reported their year of study (1% first year, 13% second year, 38% third year, 38% fourth year, and 10% other), gender (76% Female, 21% Male, 1.7% Nonbinary, 1.7% prefer not to say) ethnicity (56% Hispanic), race (1% American Indian/Alaska Native, 13% Asian, 6% Black/African- American, 10% Two or more races, 58% White/Caucasian, 11% Other race) and whether they were enrolled in a STEM major (78% STEM major, 15% not STEM, 3% plan to enroll in a STEM major, 4% Other).

The intervention group consisted of 101 students from two undergraduate microbiology courses and the comparison group consisted of 17 students from a separate undergraduate microbiology course (see Figure 2 for a summary). The imbalanced number of participants between treatment and comparison groups was unexpected and unaccounted for in our original power analysis. To infer power losses from imbalanced groups, we conducted a Monte Carlo simulation using the SimDesign package in R (Chalmers & Adkins, 2020) and compared power of a relatively balanced two-sample F-Test with sample size of 118, alpha of .05, and effect size of .15 to the same model but with the unbalanced group proportions found in this study. After 100,000 simulations, results revealed that power decreased from .98 to .83.

All participants first completed a pretest questionnaire measuring their microbiology knowledge and perceived relevance of data science for exploring problems in soil microbiology. After the pretest, learners either completed the ~60 minute module asynchronously within a three-week window (treatment group), or continued with their “business as usual” microbiology lesson (comparison group). After their microbiology lesson, participants then completed an identical post-test of microbiology knowledge, data science relevance as well as a microbiology-specific interest scale, a Data-Science-specific interest scale, a Cognitive Engagement scale, Task Value scale, and a demographics questionnaire.

Figure 2.

Summary of Phase II Study Procedures



Materials

This section describes all scales used in this study. Internal reliability for all scales at pretest and posttest were judged using Cronbach's alpha and are reported in Table 2. All specific items can be found in Appendix C-H of the Supplemental Materials.

Microbiology Knowledge. The microbiology knowledge measure used at pretest and posttest was a researcher-created 12 item scale consisting of 11 multiple choice items and 1 ranking item assessing students' knowledge of soil microbiology, including concepts and definitions pertaining to antibiotic resistance and the Tiny Earth Initiative (e.g., "What is the source of most of the antibiotics in current use?"). Each multiple choice item had between two and four response options, with one option representing the scientifically accepted value and the others representing common misconceptions. All multiple choice items were given a score of 1 for correct responses, and 0 for incorrect responses. The ranking item was given a score from 0 to 4, with one point awarded for each correct ranking among the four options. For analyses, we used an average score pretest and posttest (α = .62 and .72 respectively).

Data Science Relevance for Soil Microbiology. The data science relevance measure consisted of one researcher-created item prompting students to share whether they thought data science techniques are "relevant for addressing questions in soil microbiology?" on five response options ranging from 1 = *not at all relevant* to 5 = *very relevant*.

Interest. Participants also completed a 17-item microbiology-specific interest scale at posttest adapted from Hulleman et al., 2010, which captured microbiology-specific situated interest (e.g., "I think the material in this course is boring"), individual interest (e.g., "I think microbiology is interesting"), and utility value (e.g., "Microbiology can be useful in everyday life"). Learners responded to these items on a 7 point agreement scale. Similarly, we adapted these items to measure Data-Science-specific situated interest (e.g., "Data science fascinates me") and utility value ("Data science is useful for me to know"). All subscales had Cronbach's alphas of .73 or larger (see Table 1 for all coefficients).

Cognitive Engagement. Cognitive engagement was measured at posttest using the Cognitive Engagement scale (Greene, 2015), a 16 item measure capturing learner's willingness to devote effort to thinking analytically ($\alpha = .88$). Learners responded to statements (e.g., "I type or write out notes capturing the main ideas from") on a seven point agreement scale.

Affective Engagement. Affective engagement during learning was measured using nine positive emotion items from the Epistemic Emotions Questionnaire (Pekrun et al., 2017) in which participants were prompted to report the intensity of nine positive emotions that they experienced while learning about microbiology (e.g., curiosity, happiness, joy) on a five point scale ranging from 1 = *not at all,* to 5 = *very strong* ($\alpha = .88$).

Expectancy and Value. Expectancy and value was measured using the Expectancy-Value-Cost scale (Kossovich et al., 2015) which captured perceptions of expectancy (e.g., "I know I can learn the material in my microbiology class", attainment value ("I think my microbiology class is important"), and cost ("My microbiology class work requires too much time") on a seven point agreement scale.

Preliminary Analysis

Prior to running the main analyses, we first assessed model assumptions and confirmed whether pretest variables significantly differed by condition. We found that skew ranged from -1.6 to .62, which is acceptable (Tabachnick & Fidell, 2013). Kurtosis ranged from -.83 to .91 for all continuous variables other than: initial interest (4.53), situated interest (2.77), utility value (2.31), expectancy (3.88), and value (2.39). Because kurtosis was above threshold value for our planned analysis, we chose to use robust heteroskedastic consistent standard errors in all regression analyses (Long & Ervin, 2000; Zeileis et al., 2020).

We also assessed whether baseline measures differed by condition. Among categorical variables, Chi-Squared analyses revealed that gender, ethnicity, race, English speaking status, and STEM status were independent of condition (all $p > .117$). However, we found that both year of study ($p < .001$) and pretest knowledge ($p < .001$; using an independent sample t-test) were significantly lower in the control group compared to the treatment groups. As such, we included year of study and pretest knowledge as covariates in all analyses to control for these differences. Raw means and standard deviations by condition, and intercorrelations are shown in Table 2.

Table 2.

Descriptive Statistics By Condition and Intercorrelations Between Key Variables

	Total								Control			Treatment			Intercorrelations												
	items	α	n	Mean	SD	Min	Med	Max	n	Mean	SD	n	Mean	SD	k.pre	k.post	dr.pre	dr.post	in.int	sit.int	uv	ds.sit	ds.uv	cog	exp	value	cost
Knowledge (pre)	12	.62	117	0.7	0.2	0.2	0.7	1.0	17	0.5	0.2	101	0.7	0.2													
Knowledge (post)	12	.72	117	0.7	0.2	0.2	0.8	1.0	17	0.4	0.2	101	0.8	0.2	.62***												
Data Relevance (pre)	1	NA	116	4.0	1.0	1.0	4.0	5.0	17	3.6	1.0	100	4.1	0.9	.37***	.28**											
Data Relevance (post)	1	NA	116	4.2	1.0	1.0	5.0	5.0	17	3.4	1.2	100	4.4	0.9	.30**	.44***	.55***										
Initial Interest	8	.96	117	5.5	0.8	1.8	5.5	6.8	17	5.1	0.8	101	5.5	0.8	.28**	.38***	.31***	.33***									
Situated Interest	5	.92	117	5.9	1.1	1.0	6.2	7.0	17	5.2	1.3	101	6.0	1.0	.30***	.33***	.39***	.45***	.88***								
Utility Value	4	.91	117	5.8	1.1	1.0	6.0	7.0	17	5.3	1.3	101	5.9	1.1	.34***	.33***	.36***	.35***	.67***	.71***							
Data Science Situated Interest	3	.77	117	4.5	1.3	1.0	4.7	7.0	17	4.7	1.1	101	4.5	1.3	.07	.11	.21*	.12	.41***	.44***	.42***						
Data Science Utility Value	3	.73	117	5.0	1.0	1.0	5.0	7.0	17	4.9	1.1	101	5.0	1.0	.18*	.24**	.26**	.28**	.47***	.44***	.51***	.62***					
Cognitive Engagement	16	.88	117	3.9	0.6	2.4	4.0	5.0	17	3.7	0.7	101	4.0	0.6	.14	.23*	.30***	.34***	.63***	.61***	.59***	.27**	.29**				
Expectancy	3	.95	117	5.9	1.1	1.0	6.0	7.0	17	5.5	1.3	101	5.9	1.1	.17	.25**	.28**	.36***	.80***	.80***	.59***	.34***	.40***	.68***			
Attainment Value	3	.95	117	6.0	1.0	1.7	6.0	7.0	17	5.5	1.2	101	6.1	0.9	.31***	.38***	.37***	.41***	.82***	.83***	.76***	.35***	.49***	.67***	.82***		
Cost	4	.86	117	3.4	1.4	1.0	3.5	7.0	17	4.2	1.5	101	3.3	1.3	-.29**	-.27**	-.27**	-.17	-.39***	-.49***	-.25**	-.29**	-.15	-.30**	-.48***	-.38***	
Affective Engagement	9	.83	117	3.4	0.6	1.8	3.4	4.9	17	3.1	0.5	101	3.4	0.6	.06	.12	.26**	.35***	.40***	.48***	.30***	.45***	.36***	.47***	.43***	.36***	-.22*

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

RQ2 Results: Module Effects on Learning & Motivation

To assess the effects of the online module on microbiology knowledge, data visualization literacy, engagement, interest, and value in STEM (RQ2), we used multiple regression analyses with robust standard errors using separate models for knowledge, engagement, interest, and value. Predictors were the treatment condition, pre-test scores when applicable, as well as covariates of prior knowledge and year to adjust for baseline differences between treatment and control conditions. All continuous variables were standardized around the mean prior to regression analyses. We predicted that the module would improve learning and motivation outcomes compared with the comparison group, because theory posits that novel information can lead to conceptual change when comprehensible, compelling, and engaging (Dole & Sinatra, 1998; Lombardi et al., 2016).

A summary of the standardized regression coefficients, standard errors, and p-values for analyses can be found in Table 3 and Table 4. Generally, findings revealed significant effects of the module on posttest microbiology knowledge before and after adjusting for pretest knowledge and year of study ($\beta = 1.67$, $p < .001$, partial-$\eta^2 = .17$, with $d = 2.0$ SDs difference between treatment and control posttest knowledge). Effects on perceived data science relevance for soil microbiology were significant before and after adjusting for prior data relevance ($\beta = .66$, $p = .012$), but not after adjusting for pretest microbiology knowledge and year of study.

Table 3.
Conceptual Change Effects of the Online Module

	Posttest Knowledge β (*SE*) *p*		**Posttest Data Science Relevance** β (*SE*) *p*		
Effect of Module	**1.672***** **(0.246)** **p = 0.000**	**1.158***** **(0.289)** **p = .0002**	**0.941**** **(0.315)** **p = 0.004**	**0.655*** **(0.254)** **p = 0.012**	0.348 (0.268) p = 0.198
Compared to Control					

Prior Microbiology		0.443***			0.042
Knowledge		(0.071)			(0.095)
		p = 0.000			p = 0.662
Pretest Data				0.510***	0.497***
Science Relevance				(0.070)	(0.080)
				p = 0.000	p = 0.000
Adjusted for Year of Study	N	Y	N	N	Y

Note: **p* < .05; ***p* < .01; ****p* < .001

When the outcomes were motivational (affect, task value, and interest), findings were similar. We found that the intervention significantly promoted situated interest (β = 0.73, *p* = .014), value of science (β = 0.66, *p* = .029), and reduced perceptions of cost (β = -0.70, *p* = .013) and marginally promoted initial interest (β = 0.51, *p* = .065) and utility value (β = 0.51, *p* = .062)—but not after adjusting for prior microbiology knowledge.

Table 4.
Motivational Effects of the Online Module

	Initial Interest in Science β (*SE*) *p*		**Situated Interest** β (*SE*) *p*		**Utility Value** β (*SE*) *p*	
Effect of Module	**0.505~**	0.183	**0.726***	0.272	**0.556~**	-0.040
Compared to Control	**(0.270)**	(0.381)	**(0.290)**	(0.391)	**(0.294)**	(0.363)
	p = 0.065	p = 0.632	**p = 0.014**	p = 0.488	**p = 0.062**	p = 0.913
Prior Knowledge		0.233		0.239~		0.290*
		(0.147)		(0.140)		(0.129)
		p = 0.115		p = 0.091		p = 0.027
Adjusted for Year	N	Y	N	Y	N	Y
	Situated Interest (Data Science Specific) β (*SE*) *p*		**Utility Value (Data Science Specific)** β (*SE*) *p*		**Cognitive Engagement** β (*SE*) *p*	
Effect of Module	-0.181	-0.387	0.153	-0.220	0.400	-0.068
Compared to Control	(0.227)	(0.342)	(0.272)	(0.388)	(0.295)	(0.334)
	p = 0.427	p = 0.261	p = 0.576	p = 0.573	p = 0.179	p = 0.840
Prior Knowledge		0.101		0.194		0.104

		(0.109)		(0.126)		(0.113)
		p = 0.358		p = 0.127		p = 0.360
Adjusted for Year	N	Y	N	Y	N	Y
	Expectancy β (*SE*) *p*		**Value** β (*SE*) *p*		**Cost** β (*SE*) *p*	
Module Condition	0.415	0.086	**0.664***	0.252	**-0.700***	-0.318
	(0.289)	(0.338)	**(0.299)**	(0.387)	**(0.277)**	(0.327)
	p = 0.154	p = 0.800	**p = 0.029**	p = 0.516	**p = 0.013**	p = 0.333
Prior Knowledge		0.120		0.240~		-0.241*
		(0.124)		(0.136)		(0.098)
		p = 0.337		p = 0.081		p = 0.016
Adjusted for Year	N	Y	N	Y	N	Y

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

We also assessed whether student gender and ethnicity were significant moderators of intervention effects. Although we found that the intervention conditions leveled ethnicity disparities in posttest knowledge (i.e., main effect $\beta_{hispanic} = -1.26$, $p = .002$; $\beta_{hispanic*module} = 1.31$), this interaction was not significant after adjusting for pretest knowledge and year of study. We found no significant moderation effects of gender or gender-ethnicity interactions.

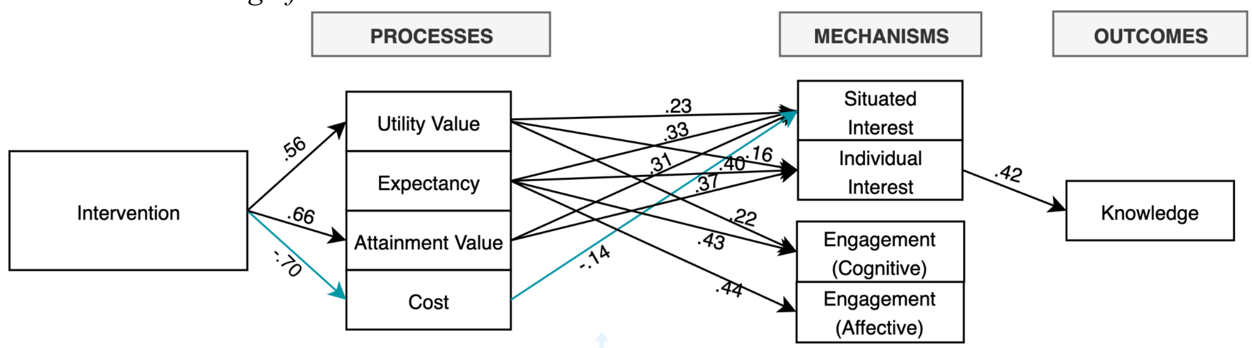
RQ3 Results: Path Analysis

We ran a path model to investigate relationships hypothesized by Hulleman & Harackiewicz (2021). Specifically, we tested the model illustrated in Figure 1, which depicts the intervention condition predicting process variables (utility value, expectancy, attainment value, and cost), followed by mechanism variables (STEM initial and situated interest), and engagement (cognitive and affective), followed by academic outcomes (microbiology knowledge). We allowed for all variables at each of the process, mechanism, outcome stages to correlate and included pretest knowledge as well as year of study was included as covariates for the microbiology knowledge outcome. All analyses were done with the "lavaan" package in R version 4.0.2 (Rosseel, 2012). The initial model had satisfactory fit at conventional levels

(RMSEA=.081, SRMR=.073, CFI=.982, TLI=.943, AIC=2209, Chi-Square=35, df=20; Hu & Bentler, 1999).

Figure 3.

Path Model with Significant Paths Shown



Note. Only paths that are significant at the .05 level are shown, blue paths are used when coefficients are negative. All variables shown represent values at posttest. All coefficients represent standardized βs. Not shown in this figure are pretest scores and year of study which were included in the model as covariates predicting posttest knowledge.

Figure 3 shows the full path model with all coefficients. Findings revealed that the intervention influenced motivation processes. As depicted in the figure, there was a significant effect of the intervention on reported utility value, attainment value, and cost with no significant effects on expectancy. These four motivational process variables were significantly associated with mechanism variables. Namely, utility value was significantly and positively associated with situated interest, individual interest, and cognitive engagement. Expectancy positively predicted situated interest, initial interest, cognitive engagement, and affective engagement. Attainment value positively predicted situated and initial interest but not cognitive or affective engagement. Cost negatively predicted situated interest, but did not significantly predict individual interest, cognitive or affective engagement. Mechanism variables then predicted outcomes. Of the four mechanism variables, microbiology knowledge was significantly and positively predicted by individual interest, but not by situated interest nor cognitive and affective engagement.

Indirect Effects

Of the significant pathways between the intervention and knowledge outcome, we found only marginally significant effects of the intervention on microbiology knowledge through attainment value and individual interest ($\beta = 0.103$, SE = .06, $p = .087$).

Discussion

In two studies, we created an online learning module for students taking a microbiology course at an HSI to engage with and draw conclusions from visualizations of authentic soil data and assessed its impacts on STEM learning and motivation compared with a comparison classroom. Below we discuss and interpret the findings as they relate to each of our three research questions (also see Table 5 for a summary of results).

Table 5.

Summary of Research

Research Questions	Data Source(s)	Analyses	Findings
RQ 1: How can a learning intervention be developed to leverage undergraduate students' motivation for the learning of soil microbiology?	Cognitive interviews with 10 students as they engaged with initial versions of module	Inductive coding methods	**Design revisions:** · Reduced extent and complexity of text to support comprehension for English Learners. · Revised text to better integrate science & data science ideas. · Revised text to better emphasize content that students found relevant (i.e., how soil relates to human health). · Introduced more interactive elements (e.g., Padlet activities and checks for understanding) · Minor revisions to survey instruments, module text, images, look and feel.
RQ 2: To what extent will such an intervention support students' microbiology knowledge, perceived relevance of data science, engagement, interest, and task value in STEM?	Pretest, Posttest, comparison group design (N=118) comparing microbiology knowledge, data relevance, affective and cognitive engagement, STEM interest, & task value.	Multiple regression analysis with control / treatment as a main predictor	**Significant effect of module *after* adjusting for baseline differences:** · Microbiology Knowledge ($p < .001$, $\beta = 1.67$, partial $\eta^2 = .17$)

RQ3: Will the hypothesized relationships between task value processes and achievement outcomes be mediated by mechanisms of interest and engagement?	Same data as for RQ2.	Path analyses to seek indirect effects	**Significant effects of intervention on motivation processes:** · Intervention Utility value, Attainment Value, ~Cost **Significant effects of motivation processes on mechanisms:** · Utility value Situated interest, individual interest, cognitive engagement, affective engagement · Expectancy Situated interest, cognitive engagement, affective engagement. · Attainment Value Situated interest, initial interest · Cost ~Situated interest **Significant effects of mechanisms on outcomes:** · Individual interest Microbiology knowledge **Indirect Effects:** · Only marginally significant indirect effects detected of the intervention on microbiology knowledge through attainment value and individual interest ($\beta = 0.103$, $SE = .06$, $p = .087$).

Note: ~ Indicates a negative relationship

Design of An Intervention to Promote Motivation for Learning Soil Microbiology (RQ1)

To address our first research question, we used design-based methods concentrating on developing a module and continuously revised it based on student feedback from 10 think aloud interviews. The intervention design was guided by theories of conceptual change (Dole & Sinatra, 1998; Lombardi et al., 2016), data visualization literacy (Borner et al., 2019), and the utility value intervention logic model (Hulleman et al., 2021). Namely, we focused our efforts on creating content that would be comprehensible and compelling for students and relevant to their lives to maximize motivation, engagement, processing of information, and potential for conceptual change (see Figure 1 for a logic model). Student feedback informed three design iterations that generally centered on revising text to be more comprehensible (e.g., easier to follow and provide vocabulary support) and more compelling (e.g., with the inclusion of health-related examples that students found relevant), as well as integrating visual supports and opportunities for interaction. Findings from this formative study ultimately resulted in an intervention that was informed by student feedback and tested in our second study.

The Intervention Directly Improved Microbiology Motivation and Learning (RQ2)

Our second study was a quasi-experimental study intended to test the efficacy of the intervention created in Study 1 for promoting learning and motivation (RQ2). We found that students who engaged with the module had significantly greater posttest knowledge when compared to a “business as usual” comparison classroom, a finding that was robust to the inclusion of a host of covariates. Intervention groups also showed improved data-literacy, science interest, situated interest, utility value, decreased perceptions of cost, and added benefits to Hispanic students compared to the comparison group, though these differences were not significant after adjusting for a few key covariates. Generally, findings are consistent with prior research showing that interventions intended to support perceptions of utility for one’s life can support motivation and achievement outcomes for undergraduate students in STEM (Hulleman et al., 2021) and that practitioners might consider framing concepts in terms of how they may be useful for students’ lives (Seyranian et al., 2023).

Intervention Indirectly Affected Learning Through Interest and Engagement (RQ3)

We also tested predictions proposed by Hulleman and Harackiewicz (2021) that interest and engagement may be important mechanisms underlying relations between task value and achievement outcomes (RQ3). We found that the relationships illustrated in Figure 1 had satisfactory fit. Indeed, psychological processes of value perceptions were significant predictors of psychological mechanisms (such as individual/situated interest and affective/cognitive engagement) which significantly predicted achievement outcomes (grades and self-reported midterm scores). Although we found only marginally significant indirect effects of the intervention on achievement through attainment value and individual interest, findings provide emerging evidence that interest and engagement may be important underlying mechanisms by which expectancy and value operate and should be explored further.

Limitations

This study has necessary imitations. First, we used quasi-experimental methods and the control condition was significantly lower in baseline knowledge, year of study, and sample size. Future studies might seek to use random assignment, or identify larger sample sizes and more balanced classrooms for comparison conditions, as many of our models did not have sufficient power to adjust for baseline differences. Second, the central intervention developed for this study leveraged several principles in a "kitchen sink" approach, that is, many teaching and learning principles were used in combination (e.g., data literacy support and highlighting relevance of microbiology data) without testing the impact of each principle individually. Future studies might use experimental research designs that isolate and test each feature separately to identify which are most beneficial for student motivation and learning.

Implications for Theory and Practice

Findings from this study have several implications for theory and practice pertaining to STEM education. Firstly, findings from this study suggest that, in order to support learning and conceptual change, scientific information that students engage with should be comprehensible and relevant. Indeed, conceptual change models (e.g., Dole & Sinatra, 1998; Lombardi et al., 2016) predict that processing of information is facilitated when content is perceived by students as compelling, comprehensible, valid, and coherent. The design of the intervention used in this study was intended to promote comprehensibility with data literacy supports, and compellingness by highlighting applications of microbiology and data science content for addressing crises in antibiotic production, which ultimately was associated with enhanced learning. As such, practitioners might consider including data-literacy supports in their data-heavy science lessons to improve comprehensibility, and identify how and why content can be relevant and compelling for students.

Secondly, findings provide emerging evidence for the idea that expectancy and value operate through the mechanisms of STEM interest (Hulleman & Harackiewicz, 2021). We found that the intervention group was associated with higher perceptions that microbiology is important (attainment value) which subsequently predicted microbiology learning, with marginally significant indirect effects after adjusting for baseline differences. This finding represents emerging evidence that individual interest is an important mechanism underlying microbiology learning. Undergraduate STEM instructors might therefore consider students' interest in STEM as a potentially important factor that is related to student's achievement, and that such interest might be facilitated by highlighting the importance of content learned in class.

Thirdly, this study represents an exploration of mathematical reasoning skills that might be leveraged to support science learning. Namely, this study investigated how promoting data literacy might feed into microbiology learning. And while the research design did not isolate the impacts supporting data literacy on its own, findings did in fact show that data literacy supports, when paired with a microbiology lesson geared towards exploring data, is associated with greater conceptual change and learning compared with a control group. As such, undergraduate science instructors might consider including data literacy support in their more traditional lessons in order to generate interest and learning in both data science and microbiology.

Fourthly, an important outcome of the design-based research portion of this study is the learning intervention itself. Researchers and practitioners are encouraged to adapt this learning module for their own work as a starting place to promote microbiology learning, motivation, and math-science integration among diverse groups of students. The integration of relevant data analysis experiences with microbiology and soil data is crucial not only for retaining students in

STEM fields but also for meeting the growing demand for data science skills in the STEM workforce (Fry et al., 2021). While existing curriculum for microbiology labs emphasize bioinformatics data analysis (e.g., Course-Based Undergraduate Research Experiences; CURE; Bakshi et al., 2019), this study provides students with a broader range of data science skills and support in applying these skills to tackle real research problems. Our pedagogical approach to might be adapted for similar. Additionally, this study highlights the benefits of interdisciplinary collaboration by combining data science, microbiology, and soil health, fostering a collaborative spirit among students and further promoting an inclusive, multidisciplined, STEM workforce.

Conclusion

This study fits into a long-term research agenda focused on supporting relevant interdisciplinary applications of STEM for Hispanic students. Findings contribute to theory and practice by (a) testing relationships hypothesized by Lombardi and colleagues' (2016) model of conceptual change, (b) testing Hulleman and Harackiewicz's (2021) process model of expectancy value interventions, (c) exploring the extent to which mathematical reasoning skills can support science learning, and (d) resulted in an intervention that can be easily shared with undergraduate science instructors, data science instructors, and with the general public.

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SUPPLEMENTAL MATERIALS

Appendix A
Cognitive Interview Protocol

Overview of Cognitive Interview Process

Introduction

- Greeting / establish rapport
- Share survey link with participant, have them share their screen
- <u>Record the interview</u>
- Read cognitive interview instructions aloud to the participant
- Remind student that they can opt out of the study at any time
- Practice exercises
- Model the think-aloud procedure
- Let the participant practice the think-aloud procedure
- Administer the interview or survey as follows:

PHASE I (Think aloud)

- Ask participant to read the questions aloud.
- Do <u>not</u> ask questions – allow the participant to think aloud as they answer the questions.
- If needed, use general prompts to encourage the think-aloud process (e.g., remember to tell me everything that you are thinking).
- Ask the participant if they are finished, or to indicate when they are finished.

PHASE II (Probing)

- Item-specific probing (see probes written in protocol)
- Goal is to understand why the participant responded the way they did.
- Designed to help describe the process used by participants in responding and identify any potential problems with the item.
- You may not need to use every probe – flexibility within structure!
- Another technique may be mirroring or summarizing what the respondent said to confirm that you understood.

Additional Probing for Feedback on Lesson

- When participants have finished thinking aloud through all intervention items, ask all of the specific questions about usability:

• What did you think [about the lesson]? • Did you hit any problems or bugs? • What would you change about the lesson to make it more engaging, relevant, or fun? • What would you change about the way information is presented in this lesson? • What was surprising? Any other thoughts you would like to share?

Complete remainder of survey

- Ask the participant to return to the survey and complete the remainder of it & continue thinking aloud.

Conclusion / Debriefing

- Answer participant questions
- THANK participant!

- Let them know compensation will be sent within a week or two, sometimes it ends up in spam, **double check email preferred for compensation**.

INTRODUCTION / PRACTICE EXERCISE

SAY:
[**Introduce yourself.** Share survey link with participant, ask them to share their screen through Zoom.]

Before we begin, please take a look at and sign the information form. Take your time and feel free to let me know if you have any questions. Note that, **if you are feeling uncomfortable, you can choose to end this interview at any time without repercussion, just let me know.**

We are creating a survey and an online lesson for a research study, and we need your help to see if we can make the survey and the lesson more engaging and easier to understand. Right now, we are currently trying out survey questions with people before scaling up this lesson up to full classrooms at [our university]. This will help us identify any problems with the questions that we created. **In other words, we need your help to make the survey questions easy to understand and to get your feedback on how to make the lesson fun and easy to use.** So really, there are no right or wrong answers.

I want to let you know that this interview will be recorded. [Record and click "save to cloud"]

The way we will try this out is by having you read each question out loud, then answer the questions and tell us what you are thinking as you figure out your answer. This is called "thinking aloud."

Since people are not used to thinking aloud, I'd like to show you an example.

EXAMPLE 1:
Suppose there was a set of multiple-choice questions that asked: "In the past week, how often did you watch the following on television? (News, Drama, Sitcoms, Documentaries, Movies)." If someone asked me to think aloud while I was answering these questions, I would start by answering the questions, and then when I was finished, I would explain what I was thinking.

(When screen displays item below, read the instructions out loud and answer questions to yourself to illustrate thinking aloud)

In the past week, how often did you watch the following on television? (News, Drama, Sitcoms, Documentaries, Movies).

News.	[None]	[1-2 Days]	[3-4 Days]	[5-6 Days]	[7 Days]
Drama.	[None]	[1-2 Days]	[3-4 Days]	[5-6 Days]	[7 Days]
Sitcoms.	[None]	[1-2 Days]	[3-4 Days]	[5-6 Days]	[7 Days]
Documentaries.	[None]	[1-2 Days]	[3-4 Days]	[5-6 Days]	[7 Days]
Movies.	[None]	[1-2 Days]	[3-4 Days]	[5-6 Days]	[7 Days]

[Model thinking aloud as you read and answer the questions.]

Now, you try it. In the past week, how often did you watch the following types of television?

If they get the idea, ask them to skip over example 2…

EXAMPLE 2:
[If they don't understand from example 1]

This question asks: "How many minutes did you talk on the telephone in the last three days?" If someone asked me to think aloud while I was answering that, I would say:

Question: How many minutes did you talk on the telephone in the last three days? ___ minutes

[Model thinking aloud as you read and answer the questions.]

Now, you try it. *How many minutes did you talk on the telephone in the last three days?*

[Have participant run through the example question.]

WHEN THE PARTICIPANT UNDERSTANDS (after the first or the second example):

That's exactly what I mean by thinking aloud. Now we are ready to get started. Do you have any questions before we begin?

You will read the text in each item aloud, and you will think aloud as you answer it. Then you will read the next item and you will think aloud as you answer that one. This will continue until I stop and go back to ask you some questions about the items you already answered. Do you understand? OK, let's get started…

PHASE I
Examples of How to Elicit Think Aloud
(Try to ask each of these at least once during the interview)

Directions

1. The directions say (e.g.), "*We are interested in the emotions you experienced when learning about soil. For each emotion, please indicate the strength of that emotion by selecting the option that best describes the intensity of your emotional response during learning.*" What does this mean to you?

Stem

2. What does the question stem (e.g.), "*I compare and contrast different concepts.*" mean to you?

Answer Choices

3. How are you thinking about the answer choices?
4. Is there another option you would like to add to or remove from the answer choices?
5. Is the order of the options helpful in giving your answer?
6. Is there another rating scale you think would be more appropriate? Why?

Appropriate Prompts in Phase 1 to Help the Respondent Think Aloud:

- *Go ahead and read the question, then answer it, we'll talk about it after you're finished.*
- *OK, I see, uh-huh, etc.*
- *Remember to **think aloud** as you answer the question.*
- *You're doing a great job **thinking aloud**.*
- *When you **think out loud**, it really helps us to understand how others approach these questions.*
- *Let me know when you are finished answering the question.*

- (If respondent struggles with answer) *Pretend this is a mail survey questionnaire you received, what would you do?*

PHASE II

After participants have "thought aloud" through cluster of items use general probes:

- OK, so what was your reasoning on that again? I just want to make sure I understand.
- *Can you say this question in your own words?*
- *What do you think this item is asking/measuring?*
- *How did you figure out your answer to this question?*
- *(If a word or phrase X is problematic) What do you think they mean by X?*
- *OK, so what was your reasoning on that again? I just want to make sure I understand.*
- *When you read this question, what did you think they were asking?*
- If you had to explain this question to a friend, what would you say they are getting at?
- So, what made you choose X, instead of say Y?

ADDITIONAL PROBING

Specific for after intervention items

- When participants have finished thinking aloud through all intervention items, ask ALL of the following questions about usability:
    - What did you think [about the lesson]?
    - Did you hit any problems or bugs?
    - What would you change about the lesson to make it more engaging, relevant, or fun?
    - What would you change about the way information is presented in this lesson?
    - What was surprising? Any other thoughts you would like to share?

Appendix B
Codebook Developed to Systematically Code Students on How to Revise The Design

Code Stem Code Name	Definition • Example Student Quote
Text	
Negative Remarks	Evidence that the individual had negative feedback to share about the text: e.g., they thought there was too much text, it was repetitive, or intimidating. • "...there are so many like paragraphs. I had to like scroll back and like, look for things."
Positive Remarks	Evidence that the individual experienced positive things about the text. • "Overall like [the text] was easy to follow, easy to understand."
Remarks that Vocab Is Difficult	Evidence that the individual had issues understanding some of the vocabulary in the module. • "like problems or issues for me?…probably they will cover the vocabulary," • "...[please change] any words that… a regular person wouldn't know."
Recommendations to Break up Text	Evidence that the individuals believed that text was extensive and should be broken up. • "I feel like if this is bolded, because then it would at least like break it up a little bit…"
Videos	
Positive Remarks	Evidence that the individuals had positive feedback to share about the videos. • "There's videos. I think those help cause you get like, a more visual like that one paragraph, visual like engages you more."
Recommend More Videos	Evidence that the individuals wanted to see more videos throughout the module. • "...maybe a couple more videos. Just a couple... I feel like videos would be more engaging."
Images	
Positive Remarks	Evidence that the participants enjoyed the images (figures, diagrams, map, infographic, picture/photo). • "I feel like… the charts, the maps, and everything, it does help like with answering some of the questions…"
Recommends More/Different Images	Evidence that the participants want more images to be added. • "I would maybe add more pictures... There were good pictures in the in it and overall, but maybe we just add pictures of something like I guess it's probably hard to add picture of microbes, since they're just microbes. But maybe what like a plate of escape pathogens..."
Relevance	
Recommendations to Make Content More Relevant	The individual recommends ways to make the content more interesting or relevant (e.g., to their life, future career, the place where they live, etc).

	• "There's literally not even any [data representing the state I live in]. So like I don't know. Maybe it would be more interesting [if there were]."
Positive remarks about relevance	Evidence that the individual shared that they found the content to be interesting or relevant (e.g., to their life, future career, place where they live, etc.) • "Well, I mean, I'm a public health major, but I'm going for nursing. So I feel like these courses will benefit me because it's something that I need to know about for my future."
Bugs	
Did Not Identify Technological Issues	Evidence that the individual experienced no bugs, or technical issues with the module. • "[Researcher: Did you encounter any bugs?] No, everything seemed, no other problems. I like that."
Identified Technological Issues	Evidence that the individual experienced technical issues with the module. • "[Researcher: Did you encounter any bugs?] Well, I mean other than the fact that I clicked the link and it didn't work."
Data Science-Specific Remarks	
Negative Remarks	Participant found the data science content (anything having to do with data: statistics, data visualizations [e.g., map-visualizations], python, R) confusing. • "I would say a big thing, maybe to include would be sources of error. • "I was confused for a lot of it, because I'm not really like the whole analytic part of it is like hard for me to comprehend personally like the maps of the United States, like a bunch of all the climates and everything like that was confusing for me, too. To be honest.
Positive Remarks	Participants found the data science content (anything having to do with data: statistics, data visualizations [e.g., map-visualizations], python, R) enjoyable. • "The most interesting was the antibiotic [data visualization]. Because… I wanna know more about like what causes like like, what's causing, like so many people to die..."

Appendix C
Microbiology Knowledge Measure

ESKAPE definition: ESKAPEs are 6 bacteria that are considered to be major threats as they comprise the majority of antibiotic-resistant infections. (*__E__nterococcus faecium, __S__taphylococcus aureus, __K__lebsiella pneumoniae, __A__cinetobacter baumannii, __P__seudomonas aeruginosa, and __E__nterobacter species*)

1. What is the source of most of the antibiotics in current use?

a) Chemical labs
b) Plants
c) Soil bacteria
d) Water bacteria

2. The pharmaceutical industry is investing most of its money in identifying novel compounds from soil bacteria.

a) True
b) False

3. Which of the following is NOT a goal of the Tiny Earth Initiative

a) Give students some research experience
b) Discover new antibiotics
c) Gain an understanding of the antibiotic crisis
d) Determine the amount of antibiotic resistance in the community

4. Antibiotic resistance means that

a) A bacterium produces antibiotics
b) A bacterium is susceptible to antibiotics
c) A bacterium is not susceptible to antibiotics
d) A person is immune to antibiotic treatment

5. Compare the various definitions and justifications below and pick the one that is most accurate.

a) The bacterium has changed physically or chemically in some way to be able to destroy the drug or avoid its action, allowing it to grow unimpeded by the drug.
b) The bacterium becomes immune to the drug; the drug no longer kills or inhibits the bacterium.
c) The person becomes resistant to the drug; the body adjusts to the dosage of the chemical and no longer responds to its action.
d) The drug is changed in the body and is inactivated physically and chemically so it no longer works properly against the bacterium.

6. What is an ESKAPE pathogen?

a) A group of 6 bacteria that are considered major threats
b) A group of 6 bacteria that comprise the majority of antibiotic-resistant infections
c) A group of 6 bacteria that have “escaped” successful antibiotic treatment
d) All of the above

7. Environmental factors, like temperature and pH, have an impact on the growth of antibiotic-producing bacteria in the soil. How do these factors influence the production of antibiotics by antibiotic-producing bacteria in the soil?

a) **Temperature and pH can influence growth and the regulation of secondary metabolism in antibiotic-producing bacteria, which ultimately determines the intensity of antibiotic production**
b) Environmental factors stimulate antibiotic production during primary metabolism in antibiotic-producing bacteria
c) All antibiotic-producing bacteria can survive drastic environmental changes, so temperature and pH are not relevant
d) Humidity is necessary for antibiotic production

8. The antibiotic resistance crisis converges with the soil crisis

a) **because antibiotics are sourced from soil, soil erosion threatens the discovery of novel antibiotics to combat the antibiotic resistance crisis**
b) because antibiotics are sourced from water, soil erosion contaminates water streams, threatening the discovery of novel antibiotics to combat the antibiotic resistance crisis
c) because antibiotic resistant microbes are in the soil and soil erosion causes increased interaction with humans and these pathogens
d) because antibiotics are sourced from plants which need the nutrients from the soil

9. Assign numbers, from start to finish, of the Tiny Earth Antibiotic Discovery Process: (Ranking item, presently organized in correct rank order)

1. Soil Sampling
2. Bacterial isolation
3. Antibiotic screening
4. Isolate Characterization and Genomic Analysis

APPENDIX D
Perceived Relevance of Data Science for Addressing Problems in Microbiology

“In your opinion, are data science techniques **relevant** for addressing questions in soil microbiology?”

1. Not at all relevant
2. Slightly relevant
3. Relevant
4. Fairly relevant
5. Very relevant

APPENDIX E
STEM Interest & Utility Value Scales

Hulleman, C. S., Godes, O., Hendricks, B. L., & Harackiewicz, J. M. (2010). Enhancing interest and performance with a utility value intervention. *Journal of Educational Psychology, 102*(4), 880.

Instructions: **Please state your agreement with the following statements.**
Participants respond on a 7-point Likert-type scale from 1 (*strongly disagree*) to 7 (*strongly agree*).

Microbiology Specific

Initial Interest

1. I think microbiology is an interesting subject.
2. I am not interested in microbiology. (Reversed).
3. I like learning about microbiology in class.
4. I think microbiology is interesting.
5. I find microbiology enjoyable.
6. Microbiology just doesn't appeal to me. (Reversed)
7. I enjoy working on microbiology problems.
8. I like learning new microbiology concepts.

Situational Interest

1. I think the field of microbiology is very interesting.
2. I think that what we're learning in this class is fascinating.
3. To be honest, I just don't find microbiology interesting. (Reversed)
4. I think the material in this course is boring. (Reversed)
5. Microbiology fascinates me.

Utility Value

1. What I am learning in microbiology is relevant to my life.
2. I think what we are studying in microbiology is useful for me to know.
3. I find the content of microbiology to be personally meaningful.
4. Microbiology can be useful in everyday life.

Data Science Specific

Situational Interest

6. I think the field of data science is very interesting.
7. To be honest, I just don't find data science interesting. (Reversed)
8. Data science fascinates me.

Utility Value

9. Data science is useful for me to know.
10. I find the content of data science to be personally meaningful.
11. Data science can be useful in everyday life.

APPENDIX F
Cognitive Engagement (Greene, 2015)

Greene, B. A. 2015. Measuring cognitive engagement with self-report scales: Reflections from over 20 years of research. *Educational Psychologist, 50*(1), 14-30.

***Instructions*: Please rate your agreement with each statement.**

1	2	3	4	5	6	7
Strongly Disagree			**Neutral**			**Strongly Agree**

1. When learning in microbiology class, I summarize the content in my own words.
2. I put together ideas or concepts and drew conclusions that are not directly stated in microbiology class.
3. I compare and contrast different concepts.
4. While learning new concepts, I try to think of practical applications.
5. I mentally combine different pieces of information from microbiology class into some order that makes sense to me.
6. I try to learn new material by mentally associating new ideas from microbiology class with similar ideas that I already know.
7. I evaluate the usefulness of the ideas presented in microbiology class.
8. I make sure I understand material that I learn in microbiology class.
9. I try to memorize the content from microbiology class.
10. I develop memory tricks (mnemonics) to help me remember the content from microbiology class.
11. I try to remember exactly what my microbiology class instructor states in lecture.
12. I type or write out notes capturing the main ideas from.
13. I copy down details exactly as they are taught in microbiology class.
14. I am very interested in the content area of microbiology class.
15. I am able to stay focused during microbiology class.
16. I have an easy time paying attention during microbiology class.

APPENDIX G
Affective Engagement (Pekrun et al., 2017)

Positive Emotions from Epistemically Related Emotions Scale (Pekrun et al., 2017)
Pekrun, R., Vogl, E., Muis, K. R., & Sinatra, G. M. (2017). Measuring emotions during epistemic activities: The epistemically-related emotion scales. *Cognition and Emotion, 31(*6), 1268-1276.

Instructions: We are interested in the emotions you experienced when learning about soil. For each emotion, please indicate the strength of that emotion by selecting the option that best describes the intensity of your emotional response during learning.

1 = *Not at all,* 2 = *Very little,* 3 = *Moderate,* 4 = *Strong,* 5 = *Very strong*

1. Curious
2. Surprised
3. Interested
4. Inquisitive
5. Amazed
6. Happy
7. Excited
8. Astonished
9. Joyful

APPENDIX H
Task Value (Kossovich, 2015)

Kosovich, J. J., Hulleman, C. S., Barron, K. E., & Getty, S. (2015). A practical measure of student motivation: Establishing validity evidence for the expectancy-value-cost scale in middle school. *The Journal of Early Adolescence, 35*(5-6), 790-816.

Instructions. Please rate the following items.

1 = Strongly disagree, 2 = Disagree, 3 = Slightly disagree, 4 = Neutral, 5 =Slightly agree, 6 = Agree, 7 = Strongly agree

Expectancy

1. I know I can learn the material in my microbiology class.
2. I believe that I can be successful in my microbiology class.
3. I am confident that I can understand the material in my microbiology class.

Attainment Value

4. I think my microbiology class is important.
5. I value my microbiology class.
6. I think my microbiology class is useful.

Cost

7. My microbiology classwork requires too much time.
8. Because of other things that I do, I don't have time to put into my microbiology class.
9. I'm unable to put in the time needed to do well in my microbiology class.
10. I have to give up too much to do well in my microbiology class.