Students' Epistemic Connections Between Science Inquiry Practices and Disciplinary Ideas in a Computational Science Unit

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Abstract: Teaching science inquiry practices, especially the more contemporary ones, such as computational thinking practices, requires designing newer learning environments and appropriate pedagogical scaffolds. Using such learning environments, when students construct knowledge about disciplinary ideas using inquiry practices, it is important that they make connections between the two. We call such connections epistemic connections, which are about constructing knowledge using science inquiry practices. In this paper, we discuss the design of a computational thinking integrated biology unit as an Emergent Systems Microworlds (ESM) based curriculum. Using Epistemic Network Analysis, we investigate how the design of unit support students' learning through making epistemic connections. We also analyze the teacher's pedagogical scaffolding moves that support such connections. This work implies that to support students' epistemic connections between science inquiry practices and disciplinary ideas, it is critical to design restructured learning environments like ESMs, aligned curricular activities and provide appropriate pedagogical scaffolds.

Introduction

Over the last few decades almost every field related to math and science has seen extraordinary growth in the incorporation of computational tools and methods as core elements of practice. This rise in the importance of computation has been recognized by STEM education communities (Grover & Pea 2013, Atkinson & Mayo, 2010, Wilensky, Brady & Horn, 2014). While most educational researchers agree that it is important to teach Computational Thinking (CT) in K-12 schools, there is still debate about what constitutes CT and how to incorporate it in pre-college education contexts (Grover, 2019).

In this paper, we view CT in the context of STEM disciplinary practices. Our work builds on Wilensky, Horn, and colleagues' work of identifying practices in STEM disciplines that sit at the intersection of computing and scientific inquiry (Wilensky, Brady & Horn, 2014; Weintrop et al. 2016). This perspective argues that incorporating CT practices in STEM classrooms will (1) bring school science more in line with the work of modern STEM practitioners, (2) broaden access to learning CT for all students and (3) are pedagogically effective for deepening the learning of mathematics and science content (e.g., Wilensky, 1999a; Wilensky and Reisman, 2006; Levy & Wilensky, 2009; Sengupta et al., 2011; Dabholkar, Anton & Wilensky, 2018).

The work discussed in this paper is part of a larger design-based implementation research (Penuel et al., 2011) project titled CT-STEM, which integrates computational tools and high school science activities to support students' learning of CT (Swanson et al., 2017). In this study, we discuss a high school biology unit for which one author was one of the lead designers. This unit was designed to foreground CT practices and engage students in Next Generation Science Standards (NGSS) science inquiry practices (NGSS Lead States, 2013). We argue for the affordances of specifically designed computational learning environments that we call Emergent Systems Microworlds (ESMs) (Dabholkar, Anton & Wilensky, 2018) to support students to strengthen connections among science inquiry practices and disciplinary core ideas.

Design framework and theory

Emergent Systems Microworlds (ESMs)

ESMs combine two design principles: agent-based modeling of complex systems (Wilensky, 2001) and the idea of microworlds associated with Constructionist perspectives on learning (Papert, 1980). We have proposed the term Emergent Systems Microworlds as a way to describe a unique way of combining these two design principles (Dabholkar, Anton & Wilensky, 2018). There are many such examples of ESMs in the literature (e.g. Sengupta & Wilensky, 2011, Levy & Wilensky, 2009; Yoon et al., 2018), but we find this terminology useful to think about and design new activities rooted in ESMs. In the context of ESM design, we use the functional definition of microworlds (Edwards, 1995) as encapsulated open-ended computational exploratory environments in which a set of concepts can be explored, through interactions that lead to knowledge construction (Papert, 1980; Edwards, 1995). ESMs are agent-based models of emergent systems that are designed as microworlds to support students' learning through explorations and investigations of those models (Dabholkar, Anton & Wilensky, 2018).

Agent-based modeling is a powerful methodology that has emerged from complex systems theory (Epstein & Axtell, 1996; Grimm & Railsback, 2005; Wilensky & Resnick, 1999; Wilensky & Rand, 2014). In contrast to more traditional mathematical modeling, which involves symbolic representations in the form of equations, agent-based modeling makes use of simple rules that define the behaviors of computational agents. Each agent has variables that describe its state, such as age and energy level. Agents' computational rules are framed from the agent's point of view. For example, an agent could be a goose in a flock of geese. As each goose follows the computational rules, regarding alignment, separation and cohesion, which results in emergence of a complex pattern - the V-shape of a flock.

The Emergent Systems Microworlds design framework is based on Restructuration theory. Restructurations use new representational forms to reformulate knowledge in various disciplines (Wilensky & Papert, 2010). Wilensky and Papert define structuration as the encoding of the knowledge in a domain as a function of the representational infrastructure used to express the knowledge. A change from one structuration of a domain to another resulting from the change in representational infrastructure is *restructuration.* In the design of ESMs, the agent-based models are the source of the restructurations. The use of agent-based models provides a powerful entry point into understanding emergent phenomenon (Wilensky & Papert, 2010). The agent-based restructurations reduce cognitive and perceptual limitations by allowing students to reason about emergent patterns at the system level by observing behaviors of agents (Goldstone & Wilensky, 2008) and allowing students to explore, investigate and reason about complex systems phenomena. Whereas traditionally students employ heuristics and formulae given to them by authority, they are now able to author their own heuristics and formulae derived from their modeling experience. Such restructurations have been demonstrated to be pedagogically effective to support the learning of several complex natural phenomena in science education (e.g., electric current, resistance, temperature, pressure, evolution, crystallization) (Sengupta & Wilensky, 2011; Wilensky, 1999a; Wagh, Cook-Witt & Wilensky, 2017; Blikstein & Wilensky, 2008).

Epistemic connections with ESMs

We hypothesize that as students engage in ESMs, they learn about the relationships among disciplinary ideas and science inquiry practices. We view such relationships among disciplinary ideas and science inquiry similar to how learning is described through Epistemic Frame Theory: as understanding the relationships among practices, identities, values, knowledge, and epistemologies (Shaffer, 2017). We operationalize four central ideas in Epistemic Frame Theory - culture, discourse, interaction, and time, as follows. As a teacher implements an ESM-based curricular unit, there is an interplay between the classroom *culture* of learning and *culture* of scientists (science inquiry practices) to construct knowledge. The classroom *discourse* is shaped by the teacher while also influenced by the design of the ESM-based curriculum. This discourse includes language, practices, values that get expressed in the space (Gee 1999) as teachers and students talk, as well as in students' responses to the embedded curricular questions. The classroom *interactions* in an ESM-based unit are students' interactions with the ESM, with each other, and with the teacher in the classroom. The curricular unit is designed with a specific *temporal progression* in mind, the progression subsumes students learning of the inquiry practices as well as disciplinary ideas. In the classroom, students construct knowledge about a disciplinary idea regarding natural selection by engaging in science inquiry practices. Such knowledge construction requires students to make connections between: Practices ←→ Practices; Ideas ←→ Ideas; and Practices ←→ Ideas. We call these connections, *Epistemic Connections*.

To understand student learning within an ESM-based curriculum we investigate the following research questions:

(1) How does the design of a computational thinking integrated biology unit support student connection-making among science inquiry practices and disciplinary ideas?
(2) How does the teacher facilitate connections among science inquiry practices and disciplinary ideas?

Research context and methods

Participants and setting

Evolution of Populations is a ten-day biology unit designed by the lead author in consultation with high school biology teachers. The unit focuses on predator-prey dynamics, competition among individuals, and natural selection (Appendix 2). The unit was taught by a biology teacher Ms. Lydia (pseudonym) in a large Midwestern city’s public school. Activities were delivered through an online curriculum portal (link removed for blinding purposes) and were split into lessons and each lesson consisted of 3-4 pages. Typically, on each page, students read a prompt with a description of a computational model and suggestions for exploration. Then, students answered 2-5 embedded assessment questions on the same page. The curricular unit built on the case of Rock Pocket Mice natural selection in the desserts of New Mexico (Dabholkar, 2019). The ESMs in the unit are built using NetLogo (Wilensky, 1999b), an agent-based modeling platform which is intentionally designed to foreground emergent systems modeling for educational and research purposes.

Figure 1. A page from lesson 2 in which students explored a NetLogo model of rock-pocket mice about the predator-prey relationship and natural selection.

Design of the rock pocket mice ESM-based unit

The Rock Pocket Mice ESM-based unit is designed by adapting a unit by Howard Hughes Medical Institute (https://www.hhmi.org/biointeractive/making-fittest-natural-selection-and-adaptation) and an AP biology lab (shared by a teacher -AP(R) Biology Lab Manual for Students, 2001). The unit consists of three lessons that progress from introducing the anchoring phenomenon to students performing scientific investigations using the ESM. The ESM simulates natural selection and adaptation in populations of rock pocket mice, which are found mainly in rocky outcrops in the deserts of the southwestern United States and Mexico.

Figure 1 shows one page of a lesson in which students explored a model (using the drop-down menu and sliders to change parameters) and answered embedded questions. Students can set composition of the initial population of rock pocket mice. Students can also set the background colors - dark, light or mixed. Predation in the model can be controlled by setting "predation?" ON or OFF; and setting value for chance-of-predation. chance-of-predation value determines the probability of a mouse dying because of predation on each click-tick. The predation probability reduces depending on how well a mouse camouflages, based on its fur coat color and the color of the surroundings. The button - "Add a mutant", adds a heterozygous mutant at a random location.

The pedagogical activities in the lessons are designed to scaffold students’ open-ended investigations of the phenomenon of natural selection in the case of rock pocket mice using the model. The ESM-based lessons on include questions to engage students in inquiry practices such as asking questions, stating an answer in the form of a hypothesis, designing an experiment, conducting an experiment, collecting data, analyzing data, arguing with evidence in data to support a claim.

Automated coding and Epistemic Network Analysis

In this study, we examined students’ responses to embedded questions in three different lessons of the unit. We coded for students’ explicit engagement in inquiry practices such as using a model or analyzing data, and explicit mentions of core disciplinary ideas such as adaptation or inheritance. We used both a top-down and a bottom-up approach to develop codes (Miles, Huberman & Saldaña, 2014). The top down codes were used to characterize students’ knowledge of CT and science inquiry practices developed from NGSS science practices (NGSS Lead States, 2013) and Weintrop et al.’s (2016) taxonomy. We used the following codes *Asking Questions and Defining Problems, Developing and Using Models or Simulations, Planning and Carrying Out Investigations, Analyzing and Interpreting Data, Constructing Explanations*. We used bottom up coding approach to devise codes for characterizing students’ knowledge of disciplinary ideas. Based on iterative analysis of students’ responses we developed the following codes, *Populations/Individuals/agents, Phenotypic Properties or Characteristics, Genotypic Properties or Characteristics, Environments, Heritability, Survival, Adaptation mechanism, Change/Mutation/Variation* (A link to the codebook hosted at a personal location is not added in this blinded version). Because the data contained 2,026 responses, we developed an automated coding algorithm using keywords and regular expressions (see Arastoopour, et al., 2019a and 2019b for a similar methodological approach), refined the coding scheme, and conducted final pairwise inter-rater reliability tests among two human raters and the algorithm using Cohen's Kappa and Shaffer's Rho (Shaffer, 2017).

Table 1: Code categories and inter-rater reliability values for each code (* Shaffer's Rho < .05)

Code Category	**Code**	**Cohen's Kappa Between Rater 1 and Rater 2, Rater 1 and Automation, and Rater 2 and Automation**
Scientific Inquiry Practices	Asking Questions and Defining Problems	1.0*, 1.0*, 1.0*
	Developing and Using Models	.92*, .91*, .83
	Planning and Carrying Out Investigations	.91*, .73*, .77*
	Analyzing and Interpreting Data	.85*, .91*, .77
	Constructing Explanations	.86*, .65, .81*
Disciplinary Ideas	Populations and Individuals	1.0*, .92*, .92*
	Phenotypic Properties	1.0*, .78*, .78*
	Genotypic Properties	1.0*, .82*, .82*
	Environments	1.0*, .79*, .79*
	Heritability	.98*, .75*, .77*
	Survival	.92*, .83*, .91*
	Adaptation Mechanism	.94*, .81*, .88*
	Variation and Mutation	.92*, .76*, .83*

To analyze student connection-making among science inquiry practices and disciplinary core ideas, we used Epistemic Network Analysis (ENA; Shaffer, Collier, & Ruis, 2016; Shaffer, 2017). In our prior work, we have applied ENA to effectively assess and visualize learners' connections among CT-STEM practices and knowledge (Arastoopour, et al., 2019a; Arastoopour et al., 2019b). In this study, we applied ENA to the coded data and operationalized connections in terms of co-occurrences among the codes in each student response. The accumulation of the co-occurrences of codes for each student was represented as a weighted network, in which the weight of the link between the codes represents how often a student linked particular science inquiry practices and core disciplinary knowledge. Using ENA we visualized the centroid of each student's network and plotted the centroids in a fixed x-y axis space determined by the ENA algorithms. We then used the same coding scheme and ENA to analyze teacher's discourse in the classroom to investigate how she scaffolded students' learning.

Results

Student progression through ESM lessons

The ESM-based unit was designed for the students to progress sequentially from (1) introduction to the phenomenon and exploring the model, to (2) learning to use the model for a scientific investigation, to (3) coming up with a question and investigating a hypothesis using the model. The same is true about progression of disciplinary ideas– from genotypes, phenotypes of the mice to understanding survival, heredity and change in the population across generations in different environment. We expect that progression would be reflected in the epistemic connections as they progressed from lesson 1 to lesson 3.

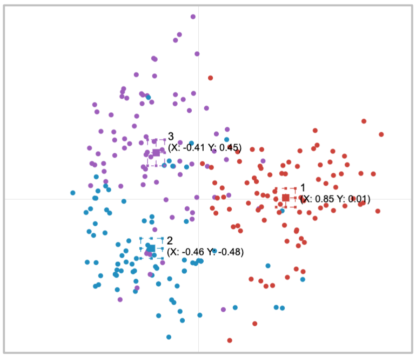

Figure 2. Centroids of networks for all students for lesson 1 (red), 2 (blue), and 3 (purple). Average is represented as square with confidence intervals. Axes represent the first two dimensions of the multi-

dimensional scaling in ENA to maximize variance in the data. The first quadrant (positive x, positive y) represents asking questions and planning investigations, the second quadrant (negative x, positive y) represents core natural selection ideas such as heritability and mutation, the third quadrant (negative x, negative y) represents constructing explanations and analyzing data, and the fourth quadrant (positive x, negative y) represents knowledge about agents and their properties.

For each lesson, students had statistically distinct epistemic connections between disciplinary ideas (DIs) and science practices (SPs), as represented by the means (Figure 2). Along the X axis, a two sample *t*-test assuming unequal variance showed lesson 1 (mean=0.85, SD=0.44, N=87) was significantly different from lesson 2 (mean=-0.46, SD=0.49, N=84; *t*(165.52)= -18.41, p=0.00, Cohen's d=2.82), lesson 1 (mean=0.85, SD=0.44, N=87) was significantly different from lesson 3 (mean=-0.41, SD=0.39, N=86; *t*(169.03)= -20.08, p=0.00, Cohen's d=3.05), and lesson 2 (mean=-0.46, SD=0.49, N=84) was **not** statistically significantly different from lesson 3 (mean=-0.41, SD=0.39, N=86; t(158.15)= 0.66, p=0.51, Cohen's d=0.10). Along the Y axis, a two sample *t*-test assuming unequal variance showed lesson 1 (mean=0.01, SD=0.43, N=87) ∫ significantly different from lesson 2 (mean=-0.48, SD=0.45, N=84; t(167.78)= 7.34, p=0.00, Cohen's d=1.12), lesson 1 (mean=0.01, SD=0.43, N=87) was significantly different from lesson 3 (mean=0.45, SD=0.59, N=86; *t*(154.76)= -5.59, p=0.00, Cohen's d=0.85), and lesson 2 (mean=-0.48, SD=0.45, N=84) was significantly different from lesson 3 (mean=0.45, SD=0.59, N=86; *t*(158.55)= -11.58, p=0.00, Cohen's d=1.77).

The plots indicated that students expressed their ideas, thoughts and reflections as responses to the embedded questions differently in each lesson. The average network representations for each lesson reveal what the differences were among the three lessons (Figure 3). In lesson 1, students connected among disciplinary ideas (di) related to the properties of the agent mice (di.agents, di.properties.phenotype, di.properties.genotype) and the science practices (sp) of asking questions (sp.asking.questions). For example, one student asked *"why did the predators caused them to be dark? How long did they survive in the dessert* [sic]*?"* (table 1) In this lesson the students were introduced to the phenomenon and began their explorations and investigations. In lesson 2, students moved forward from posing questions and progressed towards investigating more fundamental ideas required to understand natural selection. Students used the ESM to construct explanations regarding the change in mice populations across several generations under different environmental conditions. They did so by designing investigations, collecting and analyzing data. Students connected among related disciplinary ideas - di.survival, di.environments and di.heritability, and they engaged in additional science practices - sp.using.models and sp.analyzing data. In this lesson, students used the model to investigate natural selection by testing their hypotheses through data analysis.

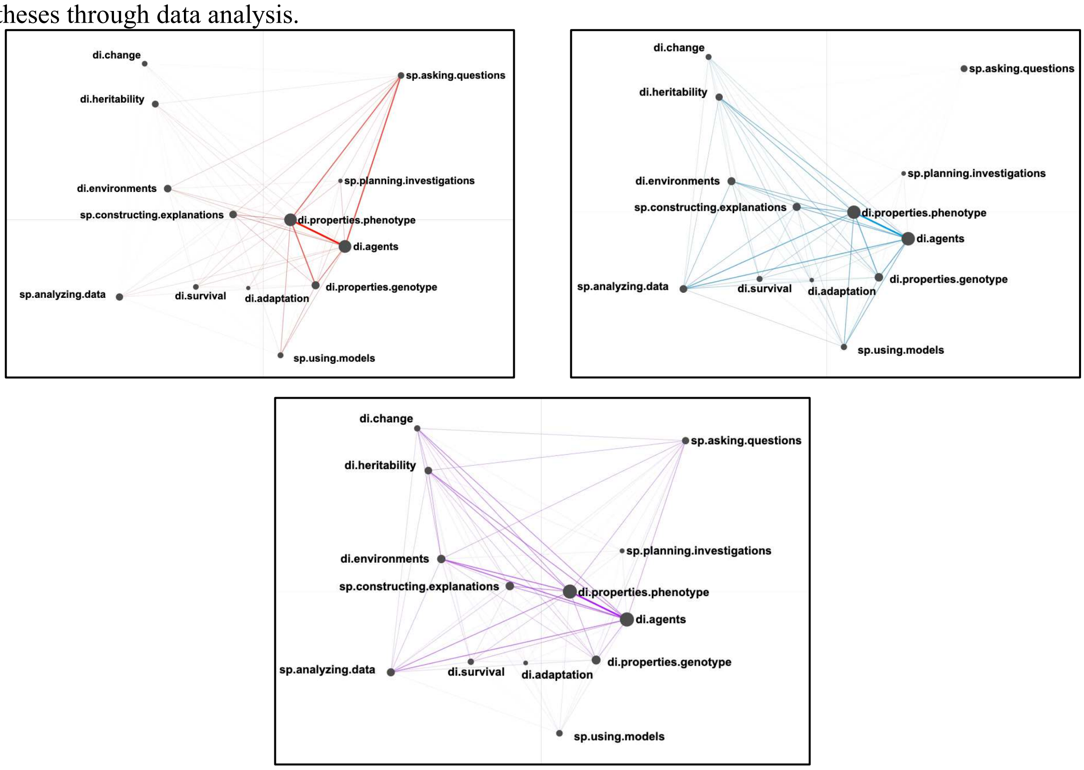

Figure 3. Average networks for all students for lesson 1 (red), lesson 2 (blue), and lesson 3 (purple).

In lesson 3, students posed their own questions and investigated various aspects of natural selection that they were interested in. The investigations included changing the initial mice populations, varying predation, and changing environment in terms of the background color. In this lesson students made connections across most practices and disciplinary ideas. The qualitative data in table 2 further illustrates how students moved from simple ideas to more sophisticated ones as they progressed through the lessons.

Teacher’s facilitation

To investigate the next research question regarding the teacher’s role in facilitating student learning we analyzed Ms. Lydia’s discourse in the classroom. In the case of an EMS-based unit, such facilitation entails scaffolding practices and disciplinary ideas sequentially throughout the unit. We created weighted network plots using ENA for Ms. Lydia’s discourse to understand how she facilitated student progression. The results suggest that Ms. Lydia’s facilitation aligns with the students’ progression. She initially facilitated asking questions and constructing explanations using models. She then asked the students to pose questions in groups and share their questions with the class (See table 2 third column, and Figure 4). She further scaffolded the use of EMS to investigate a question by setting up experiments, making observations and collecting data. Finally, she supported each group to plan investigations, analyze data, and construct explanations (Figure 4).

Table 2. Illustrative examples of student responses and Ms. Lydia’s scaffolding for lessons 1,2 and 3

	Examples of student responses to embedded questions	Examples of teacher’s scaffolding utterances during the lesson
Lesson 1 (Introduction to the case of Rock Pocket Mice)	*“why did the predators caused them to be dark? How long did they survive in the dessert?* “	*“So, go ahead and each one of you share out at least one of your things that stood out to you about what was interesting about these rock pocket mice, something that was surprising about them.”*
Lesson 2 (Natural Selection: Part 1)	*“the white mice are more popular because of the light back ground which they are able to hide from the predators the in dark back ground the dark mice are most sucsessful because they can escape and hide from the predators in the mixed back groung they both have the same population because they have there evironment they live on”*	*“So when you set it up, you should see that you have your backgrounds with just the white mice and you made a prediction as to what you would see, um, when these mice went through multiple generations of reproduction.”*
Lesson 3 (Natural Selection Part 2)	*“When we have a low predatory rate the mice with the opposite fur color to the background don't get eaten as much. This means they can reproduce at a normal rate and not be eaten as much. When you have a high predatory rate the mice that go against the background they were killed off and the mice with the proper coat have a larger chance to live, and therefor reproduce.”*	*“So every single question that is part of your guys's experiments from each team has to do with natural selection and our population of mice. So that means that we have to include what two things in our models.”*

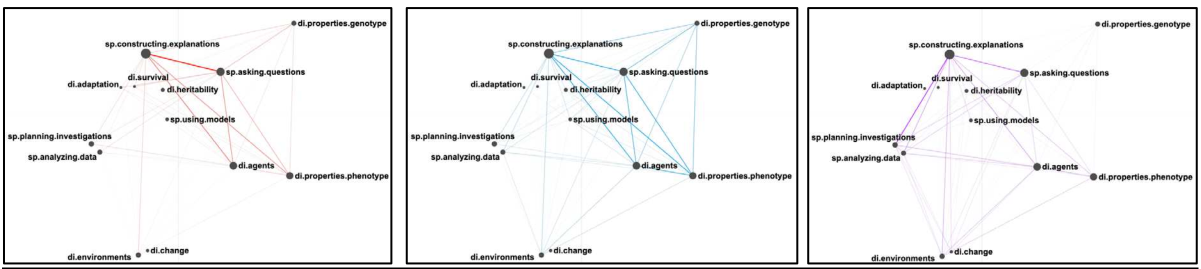

Figure 4. Networks for Ms. Lydia’s discourse for lesson 1 (red), 2 (blue), and 3 (purple).

As the unit progressed, the teacher’s epistemic connections changed as well. The epistemic connections of the teacher are indicative of her pedagogical moves for scaffolding. The changes in the teachers’ epistemic connections are in alignment with the unit design and students' epistemic connections. This implies that the teacher highlighted the relevant disciplinary ideas and science practices sequentially as the unit progressed.

Discussion

Our analysis of students' responses demonstrated that an ESM-based curricular unit can be designed such that students engage *sequentially* in computational thinking and science inquiry practices to investigate a disciplinary phenomenon. The results show that after being introduced to an anchoring phenomenon, the students posed questions that could be investigated regarding the phenomenon, learned how to use a computational model to systematically investigate specific aspects of population changes, and designed their own systematic investigations to investigate their own questions. Moreover, the results suggest that the ESM and the teacher together supported students' *epistemic connection-making* among science inquiry practices and disciplinary ideas. Although evolution by natural selection is a difficult phenomenon to understand for secondary students (Ferarri and Chi, 2008), the computational agent-based restructurations (Wilensky & Papert, 2010) in this ESM allowed students to investigate complex aspects of natural selection easily by making simple modifications in the system and observing their effects. Complementary to the ESM, a teacher's role in supporting students' connection-making is important both for foregrounding the relevant science inquiry practices and the disciplinary ideas. In this ESM unit, the teacher scaffolded students' investigations of different aspects of the underlying phenomenon to create opportunities for them to discover emergent patterns regarding the disciplinary ideas, such as a mutation for dark-fur color spreads in the population only if there are predators and the environment is dark (See table 2 - student's response to a question in the lesson 3).

Thus, this ESM-based curricular unit consisted of interactions among the ESM, students, and the teacher to create a classroom culture of scientific learning that was rooted in scientific Discourse. This view is aligned with Gee's (1999) notion of a big-D discourse that includes language, practices, values and with Shaffer's (2017) epistemic frames in terms of learning as an enculturation process that takes place through Discourse interactions over time. This study implies that to support students' epistemic connections between science inquiry practices and disciplinary ideas, it is critical to design restructured learning environments like ESMs, aligned curricular activities and provide appropriate pedagogical scaffolds. Designing for such restructured learning environments and pedagogical strategies becomes even more critical when integrating for some of the advanced science practices such as computational thinking into science learning.

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