Infect, Attach or Bounce off?: Linking Real Data and Computational Models to Make Sense of the Mechanisms of Diffusion

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Abstract: This study explores how the interplay between data and model design shifts 6th graders' students' ideas about diffusion as they build a range of models ("paper and pencil" and computational models). We present a new web-based environment and approach that integrates model-based and data-based features in the same display which facilitates the comparison of models and real-world data. Further, we illustrate how this environment and approach lead students to converge on one canonical scientific model.

Introduction and Background

Modeling has become a core element in scientific practice (Harrison & Treagust, 2000, Pluta et al., 2011; Halloun, 2011). Data plays a fundamental role in the development and evaluation of scientific models, anchoring the modeling process (Fuhrmann et al., 2018; Schwarz et al., 2009). However, model-based practices remain largely separated from data-based ones in science classes. Recent work shows that linking experimental data and scientific models in science activities has strong potential to improve student learning. For example, activities designed using Bifocal Modeling (Blikstein et al., 2016), which enables real-time model and experimental data comparisons, can support conceptual understanding, modeling, and meta-modeling competencies (Blikstein et al., 2016; Fuhrmann et al., 2018). Other researchers suggested that interlocking models with one another to draw attention to microscopic entities and their behaviors supports meaningful practice (Georgen & Manz, 2021). Gouvea & Wagh (2018) showed that coupling experiments and modeling in learning activities helps students learn how to engage in scientific practice by focusing on the goals of their investigations, allowing for comparison and triangulation. Much of the existing research on integrating modeling and data practices has involved students using pre-designed models. Little work has focused on students designing their own computer models using data to validate their models. This research is needed to understand the learning opportunities that arise from comparing real-world data and computational models, and, per the conference theme, how innovative technologies can support more effective science learning experiences.

In this paper, we ask how the interplay between data and model design shifts 6th-graders' ideas about diffusion as they build a range of models and refine their explanations based on data. We present a web-based environment and approach that integrates model-based and data-based features in the same display, facilitating the comparison of models and real-world data. Further, we illustrate how the environment and approach lead students to explore the interplay between observed data and the designed model during a unit on diffusion.

Methods

Design, settings, participants & instructional sequence

This study seeks to investigate ways to make computational modeling a sustained practice in middle school classrooms. We developed a domain-specific block-based online modeling environment based on scientific modeling research and previous studies on linking model-based and data-based practices (Blikstein et al. 2016; Fuhrmann et al., 2018; Gouvea & Wagh, 2018). The domain-specific blocks make the computational modeling accessible for students to focus on testing and refining their ideas about mechanisms underlying phenomena (Kahn, 2007; Wagh & Wilensky, 2017; Wilkerson, Wagh & Wilensky, 2017). Figure 1 shows the modeling platform, with the model and the display of the experiment side-by-side. This paper uses data from a pilot study with 43 students from two 6th-grade classes taught by the same science teacher in a middle school in California.

We designed the diffusion unit based on the Bifocal Modeling framework (Blikstein, et al. 2016). Students worked in pairs over five class periods. First, they conducted an experiment in which they compared the rate of spread of ink in hot and cold water. They ran two iterations and documented their measurements before plotting the data. Next, they designed a paper model to explain how dye spread in hot and cold water. Students then used a computational modeling environment to implement and revise their paper models. Finally, they tested their various models by comparing models' behavior with the experiment to select the model that best explained diffusion. Through class discussions, students eventually converged on a single model.

Figure 1

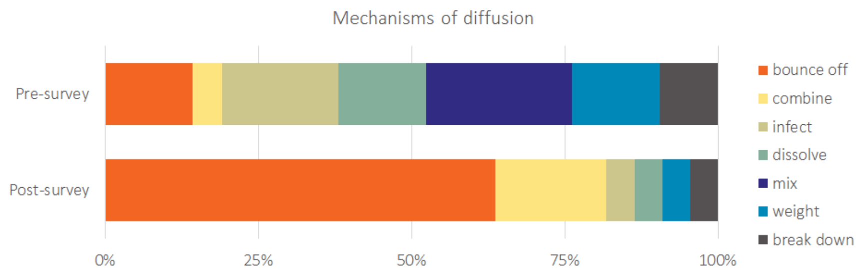
The computational modeling environment

Data sources and analysis

Data included observation notes, student artifacts, and pre/post-tests. We analyzed whole-class and student-pair data. In the observation notes, we identified critical junctures when students were, (1) constructing conjectures or explanations for the phenomenon, and (2) comparing the experiment and model. We analyzed open-ended responses to see how they shifted from pre to post. We focused on the action words students attributed to the process of diffusion (e.g., spread out, bounce off, infect), indicative of mechanistic reasoning about the phenomenon (Russ et al., 2008). These terms also align with the programming blocks in the environment. Our initial rubric was developed through open coding and further refined through reference to 10 example responses. Initially, our agreement was 60%, but we reached 89.12% agreement after several cycles of refinement.

Figure 2

The mechanisms of diffusion as reflected in pre- and post-test open-ended answers



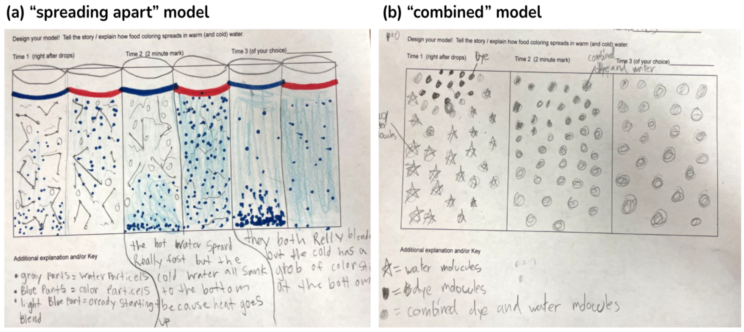
Results

Results from pre- and post-test analysis (Figure 2) showed a shift in the mechanistic language students used to describe ink spread. At the pre-test, student responses varied greatly. By contrast, in the post-test, a majority of students drew on the "bounce off" model, a canonical explanation for diffusion. For example, one student said on the post-test: *"The paint particle will bounce off the water particles, making it spread around. If it was in cold water, it would move slower than in hot water. The paint will sink before it starts spreading."* Below, we examine how this shift in language might have come about through the instructional sequence.

1. *Generating ideas for how ink diffuses in water:* In their paper models, students drew their explanations of experimental results. While students did not talk about particles to describe the phenomenon during the experimentation phase, they included particles in their paper models (e.g., mentioning type and color of particles). After completing this activity and discussing their ideas, students began to converge around two potential models: a "spreading apart" model that did not directly explain how particles interact with each other, and a "combined" model, in which dye particles and water particles combine to create larger particles.

Figure 3

Students' "paper and pencil" models: a. the "spreading apart" model, and b. the "combined" model

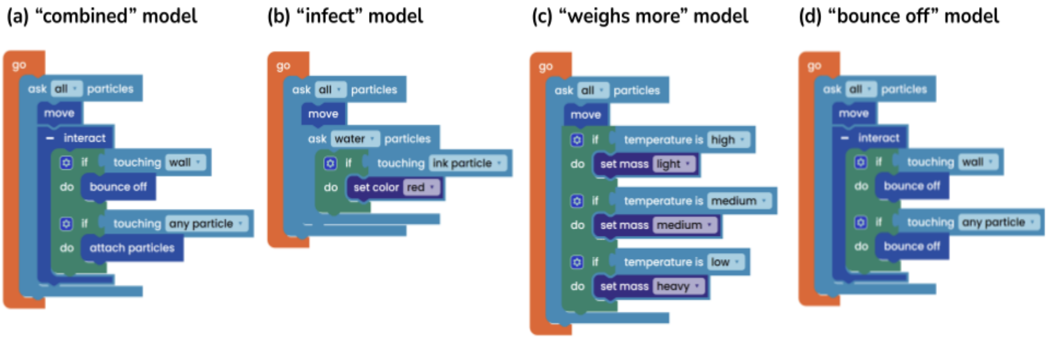


2. Translate from paper to computer, discard ideas that cannot be explained based on experiment, create new models (Figure 4). Students who drew the "combined" model used the code to create the same model (Figure 4a). When running their model, they noticed that the particles in their model attached to each other when interacting, resulting in big blobs. After comparing their model with the video data, this student pair realized that these blobs were missing from the real experiment and therefore discarded the "combined" model. These students explored other more ways to explain the dye behavior in the water using the modeling environment.

3. Converged on three candidate models. At a class level, students converged on three candidate models: the "infect" model (color particles infect water particles, which then turn blue; Figure 4b); the "weighs more" model (particles are heavier in cold water than in hot water; Figure 4c) ; and the "bounce off" model (particles spread by bouncing off each other, and they bounce off at different speeds according to temperature; Figure 4d).

Figure 4

Students' design of four models: a. "combined" model, b. "infect" model, c. "weighs more" model and d. the "bounce off" model.



This persistence of three models created noticeable tensions in the classroom. Students are used to being given the correct answer by the teacher at this stage rather than seeking it themselves. Additionally, the teacher was concerned about students using incorrect models and anxious to tell them how diffusion is defined. Nonetheless, the students and the teacher had to figure out how to navigate the situation by running additional experiments.

4. Converging on one model. To resolve the situation, students discussed with their partners potential experiments that could help prove or disprove their models. For example, to disprove the "weighs more" model, students came up with an experiment in which they used a scale to weigh the water when it was hot or cold; they discarded the model when they noticed the weight was the same. To evaluate the "infect" model, they decided to boil the diffusion water to examine the condensation on a cold plate; since the evaporated water was transparent, students agreed that the dye had not infected the water molecules and then discarded this model. Students in this class thereby converged on the "bounce off" model, which is the canonical explanation of diffusion.

Conclusions

Our findings indicate that creating models with real-world data provides students with learning opportunities that would hardly arise if they focused on model-based and data-based practices separately. We observed a shift in the mechanistic language students used to describe diffusion, shifting towards language aligned with a final canonical model. Contributing to existing work on how such convergences occur in classroom settings (see Lombard &

Weiss 2018 for a review), our findings suggest that the juxtaposition of video data of a real experiment and the model facilitated the process of generating multiple models, followed by subsequent comparison, evaluation, revision, and rejection. The scope of this paper did not allow for analyses of how the teacher guided this convergence, though previous research suggests significant influence (Millar, 2010). In future work, we intend to continue to examine the types of learning opportunities that arise from comparing real-world data and computational models, the conditions under which such opportunities arise and what designers and educators need to do to scaffold students' learning while using models authentically as tools of inquiry. Such lines of inquiry could additionally explore the ways that students' model building shapes their perception of science practices and of their agency as scientists.

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