Bifocal Modeling: A Study on the Learning Outcomes of Comparing Physical and Computational Models Linked in Real Time

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ABSTRACT

Computer modeling has been successfully used in a large number of distinct scientific fields, transforming scientists' practice. Educational researchers have come to realize its potential for learning. Studies have suggested that students are able to understand concepts above their expected grade level after interacting with curricula that employ multi-agent simulation. However, most simulations are 'on-screen', without connection to the physical world. Therefore, real-time model validation is challenging with extant modeling platforms. I have designed a technological platform to enable students to connect computer models and sensors in real time, to validate and refine their models using real-world data. In this paper, I will focus on both technical and pedagogical aspects, describing pilot studies that suggest a real-to-virtual reciprocity catalyzing further inquiry toward deeper understanding of scientific phenomena.

Categories and Subject Descriptors

K.3.1 [Computers and Education]: Computers Uses in Education

General Terms

Design, Experimentation.

Keywords

Computer modeling, sensing, constructivism, physical computing, bifocal modeling.

1. INTRODUCTION

Fifteen years ago, few would have predicted that children would be doing advanced robotics in middle-school. Indeed, since the seminal work by Papert, Martin, and Resnick [16, 19], the creation of the Lego Mindstorms platform, and the appearance of robotics competitions across the country, robotics has become a common activity in public and private schools. However, one crucial component of the revolution predicted by its proponents is still far away – its integration with the normal school curriculum. Robotics activities are often too focused on competitions and prescribed, standardized "challenges," and ended up being segregated to after school programs. In most schools, robotics teachers conduct activities regardless of what happens in science or math classrooms.

At the same time, science classrooms and laboratories are not well suited to support students for authentic scientific inquiry, developing and investigating their own scientific hypotheses and projects. For example, a student examining an acid-base reaction in a laboratory might identify the chemical elements involved and even hypothesize as to their proportions and concentrations, but the investigation cannot dive deep into chemical mechanisms. Later, in the classroom, he will learn about chemical equations and theories which bear little resemblance, in terms of scale and mechanism, to the phenomenon observed in the laboratory. Bifocal Modeling [1, 2, 5, 6] is a framework to link these disconnected types of activities and environments (computational manipulatives/sensors, science laboratories, and theoretical content in science), providing continuity between observation, physical construction of artifacts, and model-building. As this modeling platform enables seamless integration of the theoretical/computational models and the physical world, allowing modelers to focus simultaneously on their 'on-' and 'off-screen' models, I termed it *bifocal modeling*.

When building a bifocal model, students have three main tasks. First, they build a computer model of the phenomenon using various computer modeling platforms (in particular, I use NetLogo [22] in my studies). This model should encapsulate students' hypotheses about a given scientific phenomenon. Second, students use electronic sensors and low-cost analog-to-digital interfaces, such as the GoGo Board [21], to build their own sensor-equipped "science lab" to collect data about the phenomenon. Finally, students run both systems connected in real time to validate, refine, and debug their hypotheses using real-world data. The computer screen becomes a display for the computer model, which is a proceduralization, through programming, of equations, text, or other representations of scientific content, and the actual phenomenon, which is discretized and measured by means of sensors and other laboratory apparatus (see Figures 1-3, for models of an acid-base reaction, Gas Laws, and heat transfer). Because the computer models are carefully constructed to imitate the phenomenon's visual language, the bifocal methodology minimizes interpretive challenges. That is, the seen and the hypothesized are displayed such that their perceptual differences are backgrounded and, therefore, their procedural differences are more likely to be revealed. By thus utilizing the power of computation and representation, bifocal modeling constitutes a multi-disciplinary research tool that offloads aspects of both the interpretive and

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menial burden of scientific practice, freeing cognitive, discursive, and material resources that can thus be allocated toward validation of the hypotheses.

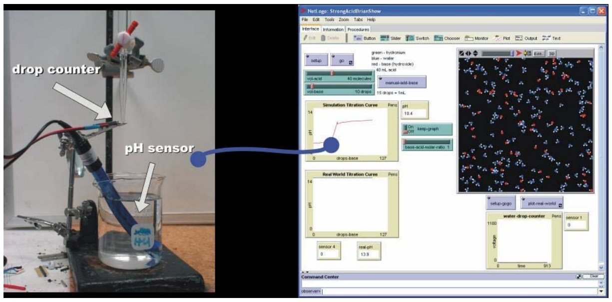

Figure 1. A model of an acid-base reaction, with the physical apparatus (left) and the computer model (right), which compares the pH 'measured' in the two models and exhibits the values in real-time for easy comparison.

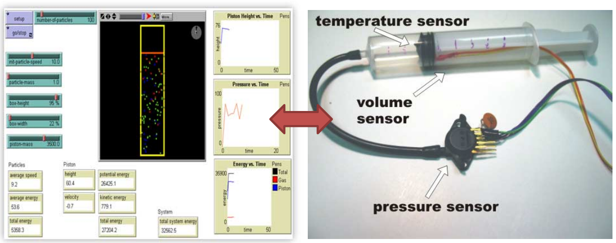

Figure 2. A model of a gas laws model, with the physical sensor-enabled syringe (right) and the computer model (left). When students press the physical syringe, the virtual syringe moves accordingly, and the students can compare the pressure measured in both.

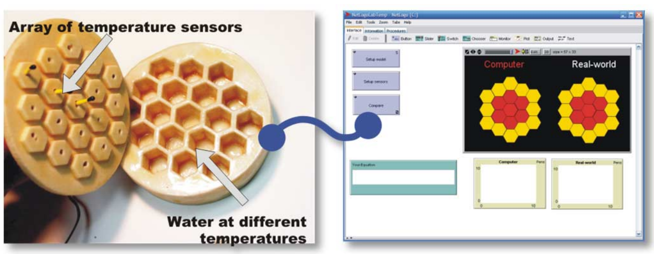

Figure 3. A model of heat transfer, with the physical model with multiple temperature sensors and hexagonal water receptacles (left), and the computer interface showing a side-by-side real-time visualization of the physical and the computer data (right).

Investigating novel ways to use computational representations and tools is timely because the use of computational models of scientific phenomena has become an increasingly viable option for classroom science learning as technology and accessibility improve. There is a large body of literature on the use of virtual models to display data, simulate complex phenomena, and permit student experimentation in domains that might be costly, impractical, or dangerous [9, 11, 12, 17, 18]. The potential of a combination of virtual and physical models to aid science learning has been documented for a wide range of ages and domains. For instance, Liu and collaborators [14] explored high school students' understanding of chemistry concepts. They found that the combination of a virtual model and hands-on lab activity was more effective than either alone, balanced for time-on-task, in promoting students' conceptual understanding of the gas laws. Recent studies have also investigated the importance of the sequencing of physical and virtual model activities on student learning, with the general result that better learning resulted from the virtual experiment following a physical one [10, 20].

However, there are two under researched areas. First, the literature has focused almost entirely on pre-designed physical and computer models. Pre-designed models can scaffold and direct students to attend to relevant problem information, but they fail to give students opportunities to evaluate the assumptions and limitations of the models themselves [16]. Creating and critically evaluating models is an important part of scientific practice, and is being increasingly recognized as a valued educational goal [3, 4, 10]. Second, the literature has also under-explored the potential for deeper support of student comparison between the physical and virtual models. Smith and collaborators [20] noted that scaffolds in the virtual model, or direct data-sharing between virtual and physical, could help students to see the similarities and differences between model and reality. However, there has been no work studying physical and computer models connected in real-time.

In this paper, I present pilot studies that demonstrate a pedagogical framework to augment the comparison between real and ideal systems as an avenue to deeper understanding of scientific phenomena. In the first study, high school students built virtual and physical models of bacterial growth in order to learn content knowledge, computational thinking, and critical meta-modeling skills. Our main research questions were: (1) how do students' understand the mismatch between idealized virtual and physical models?, and (2) how do they decide which variables and phenomenal factors are necessary to include in their own theoretical models to match the real-world data? In the second set of studies, I examined different models of implementation of bifocal modeling in classrooms, from more open-ended themes to more constricted tasks. I investigated many different formats of implementation in which I varied the topic (Biology or Physics) and the amount of model construction (students building their own models versus students being presented with ready-made models).

2. RESEARCH SETTING

In Bifocal Modeling (BM) activities, the most common software to implement virtual experiments has been NetLogo [22], a free and open-source environment for agent-based modeling. A NetLogo model typically consists of a set of autonomous agents (such as gas particles or people at a party) moving through a world and interacting to produce emergent outcomes. Students define the variables held by the agents and the world and specify a set of rules for agent-level behavior, such as "if two gas particles collide, they exchange energy and bounce off each other." Their goal is to build a model whose behavior matches the data they collected. This challenge encourages students to refine their content knowledge as they iteratively improve their virtual models, and to question the validity of their own representational choices. A student, for instance, trying to match a computer model of Newtonian motion and a real experiment may be forced to confront the existence of a missing friction coefficient, to determine how to measure motion using a given set of sensors, or even whether to model an object as a single unit or as a collection of atomic particles. In this way, BM can serve as a method to learn scientific content, modeling skills, and scientific research methods.

As a BM activity comprises many different tools, techniques, and classroom facilitation, there are multiple possible formats and phases for its implementation. These are the four major components of a BM activity, which could be present or ordered in different ways:

A. Research - In each study, students were encouraged to use external learning resources, such as the web or books, to gather initial information about the phenomenon. The format of this phase was dependent on the context of the study and students' previous knowledge about the phenomenon. The general goal of this phase was to give students baseline information about the normative representations of the phenomenon under scrutiny.

B. Design - Within a guiding theme (e.g., gas laws), students select variables that they want to explore, make hypotheses about what they will observe, and design physical and virtual models that can potentially answer those hypotheses. In designing the virtual model, students typically define the possible variables, and conceptualize micro-rules or equations to describe the phenomenon.

C. Build (program or develop)- Students construct physical models (e.g. a ball and ramp, a Petri dish filled with agar and bacteria, a system with interconnected beakers with different substances) and virtual models (e.g. a physics model of gravity and friction, an agent-based model of bacteria growth, or a computer model of diffusion) that will capture the phenomena under study.

D. Interact - Students interact with their physical models by direct observation and collecting data using embedded sensors. Similarly, they interact with the virtual model by changing parameters, running the model, observing the results, and recording data.

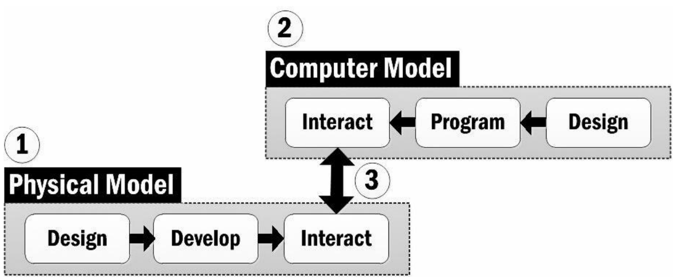

Figure 4. Components of a Bifocal Model and activity: (1) The physical model, (2) the computer model, (3) the comparison phase.

3. METHODS

In this paper I will present four BM studies conducted in our lab. I will describe the first study (Biology) in detail, and discuss in much more brief terms three other implementations of Bifocal Modeling activities (Physics, Chemistry, Open-ended). We generally employed a design-based research framework in which implementation and redesign are closely coupled [7, 8]. The four modes of BM implementation are visually summarized in Figure 5. The rectangles in black indicate the design elements used. (Note that the "Research" element was not included in the figure, but all of the activities began with students engaging in research.)

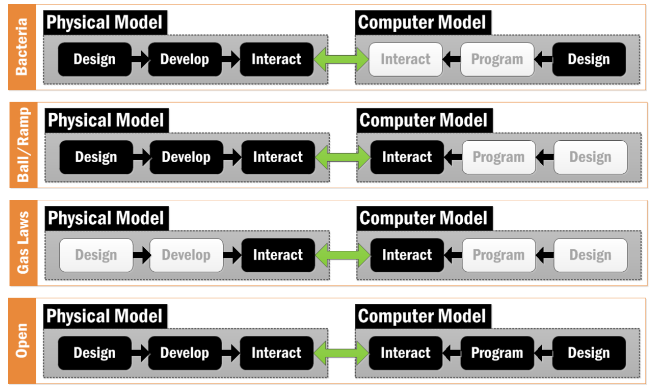

Figure 5. A visual summary of the different Bifocal Modeling activities, showing the blocks I used in the four studies (in black).

3.1 First Study: Biology

The first study was conducted with four female high school students. The topic of the workshop was bacterial growth. The study lasted for a total of about five hours, split across three afternoon sessions. Students' first task was to grow real bacteria using supplied tools. They were also shown a short video about bacteria growth in a petri dish. Then, the students in groups of two did internet research on the bacterial growth curve. For the final assignment, the authors conducted a variation of "paper modeling" [3, 4] session in which students collectively designed an agent-based model of bacterial growth on a whiteboard (Figure 6 and 7). In the paper modeling activity, students in small groups create a detailed block diagram of all aspects of a computer model and simulate a few runs (without a computer). For example, students define all the needed variables for the model, all the agents and their properties/rules, all possible interactions between agents, etc. The facilitator helps students translate their ideas into the proper "code blocks," but once students understand the general idea, the role of the facilitator transitions to becoming more of a documenter of students' ideas. Paper modeling offers some advantages over full-fledged modeling. Namely, students only need a short introduction to the programming language, and the time is spent almost entirely on conceptual programming rather than on the minutiae of writing code. Evidently it is not equivalent to programming, but in previous work [4] I have shown that it is possible to map ideas and concepts from paper modeling to what students would accomplish when doing full-fledge coding.

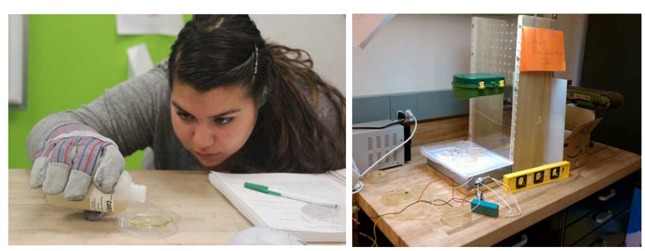

Figure 6. Students preparing their petri dishes to grow bacteria (left), and the time-lapse camera apparatus (right).

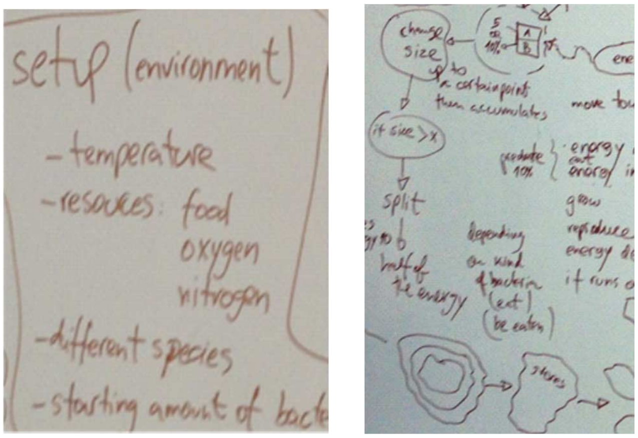

Figure 7. Some small snapshots of the "paper modeling" activity, in which students collaboratively created a flowchart of an agent-based model of bacterial growth.

3.2 Second study: Physics

In the second study, 11 high school students (4 females and 7 males) studied Newton's laws by investigating the time it takes for a ball to travel down a ramp. The study lasted for 6 hours. Students were first asked to build a physical model to investigate the variables affecting the time it took for a ball to roll down a ramp. In groups of two or three, they built ramps and attached light and infrared sensors to detect the position of the balls. For this pilot study, I shortened the activity of designing a virtual model and let students investigate and interact with a pre-made NetLogo model. It enabled students to simulate a ball rolling down a ramp and vary parameters such as ball mass and ramp angle without them having to program the model from scratch. Finally, the staff led the students in comparing the behavior of the virtual and real models – particularly, to observe that the virtual model predicted that ball's mass had no effect, while the empirical data suggested otherwise.

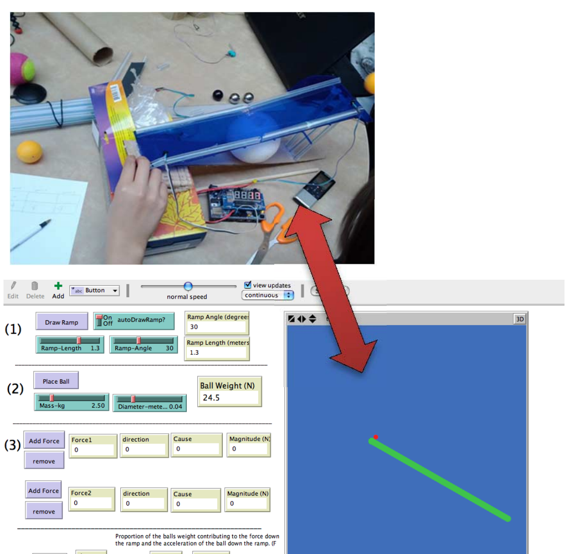

Figure 8: One of the projects in the "ball and ramp" study, in which students had a kit of parts to build their ramp (above) and then compared it with a computer model programmed in NetLogo in which students could change several parameters.

3.3 Chemistry

In the third study, students investigated the relationship between gas volume and pressure in a closed system. This study was conducted with the same group of school students as the previous study, and for the same amount of time (6 hours). Students were asked to interact with a pre-built syringe system with pressure sensors, and collected data about the relationship between pressure and volume. Next, I provided a NetLogo computer model of the gas laws, with which students could interact and see the behavior of gas particles in a container with a moving piston. As the volume of the physical syringe changed, the computer model varied accordingly, and the students compared the match between the pressure sensor values and the results supplied by their virtual model.

3.4 Open-ended

In this study, students could freely choose their topic of interest. The group had 12 freshmen high school students (11 male, one female), and was conducted as an after school program in a school in Moscow, Russia. Over three days (24 hours total), they were supposed to build a physical model, a computer model in NetLogo, and write a report about the comparison about them.

Figure 9 shows one typical project, a model investigating liquid diffusion, with the physical model on the left and the computer model on the right.

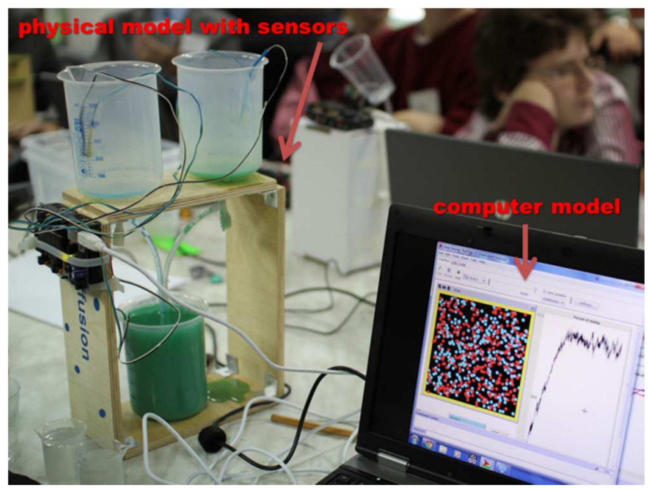

Figure 9: One of the projects in the 'open-ended' workshop. Note the physical model of diffusion on the left, with sensors, and the computer model in NetLogo on the right, connected in real time. The colored dots represent particles of two different liquids mixing, and the graph shows the change over time in a "mixing index".

4. DATA AND DISCUSSION

In the discussion, I will mainly focus on the first study. I will also discuss one dimension of the data and its presence within the four studies

I will start with a commented narrative of several classroom episodes centered on the perceived and hypothesized affordances of BM in the first study- the bacterial growth: (a) resolving model mismatch, (b) converging on appropriate variables, (c) critically evaluating the assumptions of models, and (d) translating between micro and macro perspectives.

4.1 Iteratively improving the virtual model to resolve mismatch

Overall, the group's method was to "run" their whiteboard virtual model in order to see how the bacteria grew, to compare the results to their goal of the growth curve from the physical data, and to resolve the perceived differences between the two by adding rules and variables to the virtual model. They repeated this process a total of four times in the 1.5 hours of the session, developing an increasingly accurate model in the process (figure 3).

- add bacteria, food, moisture, temperature
- add rule: bacteria move around randomly
- RUN MODEL: results were a flat growth curve
- add food rule: bacteria absorb food and moisture
- add waste rule: bacteria release waste
- add reproduction
- RUN MODEL: results are exponential growth and no death
- add death rule: if bacteria don't get food/moisture, they die
- RUN MODEL: results were exponential growth and then death
- add lag phase rule: first generation takes longer to multiply

Figure 10: A chronological list of the additions the students made to the model, and the instances in which they ran it. The results of each run prompted a subsequent rule addition that made the model more accurate.

For example, a student observed at one point after "running" the virtual model that their growth curve was increasing exponentially from the start. She noted that this was not correct, because the real growth curve had an initial flat "lag phase" before beginning to grow. After a moment's reflection, she remembered that this was because real bacteria have an initial phase of settling into a new environment before multiplying. She said "We need to make a rule that it takes time before the bacteria grow." Another student chimed in, saying that this would have to be different from a maturation period for individual bacteria, because it would apply only to the first bacteria on the dish. After more discussion about how to code the lag phase in their system, they came up with the following rule: "If a bacterium is in the first generation, it has to wait two time steps before reproducing." Upon running the model again, students could see from the resulting curve that they had successfully created the lag phase. The students went through a similar process to add all of the variables in their model.

4.2 Converging on appropriate variables

When the students were searching the web for information about bacteria, they collected and wrote down a great deal of information that was not necessary for the modeling task they were given. For example, some students noted that bacteria are prokaryotes, eat many types of human food, and live in a range of conditions. However, during the whiteboard virtual modeling session, the students only included variables that were necessary to define the shape of the growth curve - food/moisture, waste, and bacteria health. Global variables like temperature and oxygen affect bacterial growth, but the dynamics of the curve assume that these global variables are constant or the variations are too small. The fact that the students left these variables out without prompting suggests that they implicitly understood this instance of a controlled variable.

Students also made decisions regarding the granularity with which to describe variables. One student noted multiple types of bacteria nutrients in her web research, but went along with the group in representing food as a single variable of just one type. When asked about this issue, she replied that "I don't need to be that specific for this model."

4.3 Critically evaluating the assumptions of models

In addition to learning about the relevant variables for modeling bacterial growth, the students in the Bifocal Modeling workshop, also, reflected on the underlying assumptions of their models themselves - in this case, their representations of space and time. Space is represented in NetLogo as a grid of square "patches", units of space that can possess variables like location or food concentration. This patchwork representation of space was explained to the students at the start of the whiteboard modeling session, but at the time of introduction it was only relevant as a way to explain how to represent environmental variables such as food. However, as the session progressed, the students noticed that their bacteria were scattered randomly across the surface in their model, and filled the entire surface uniformly as they multiplied. In contrast, the real bacteria that they grew formed small circular spots. In order to explain the difference, students engaged in a discussion about how far bacteria can move, which quickly led to the question of the size of whole square grid itself. As one student put it, "This square could be a whole dish, or it could be just a tiny spot in the real Petri dish… if we were looking through a microscope, zooming in, they [the bacteria] will move much more. " At the end of their discussion, they decided that it was up to them to define the size of the virtual world they designed, if they kept thing in proportion. In previous work [2] I have observed students reconsidering space in their computer models and engaging in sophisticated discussions about sampling, relative size of the molecules in relation to containers, and similarity concluding that the arbitrary sizes of the model "seemed" unrealistic but were still useful modeling abstraction for their projects.

Time in NetLogo and in the whiteboard model was represented as a series of discrete steps called "ticks." While discussing the proper time delay for the lag phase, one student realized that they had no agreed conversion between ticks and real time. She asked, "Do bacteria get food and moisture each minute? Each hour? Each day? Right now we are just doing this with ticks... how can we translate the tick into real time?" At the end of another discussion about the time scale of bacteria growth in the real world and in NetLogo program, the students decided that if bacteria can multiply every 20 minutes, they will agree that one tick in the virtual world equaled 20 minutes in the physical world. Though they did not entirely resolve their questions about representing time and space in their model, the students were asking the "right" questions; that is, they were asking about the assumptions that models make about the world, which are at the heart of scientific critical thinking, and again understanding that even seemingly unrealistic assumptions or abstractions can be "good enough" for their modeling purposes.

4.4 Translating between micro and macro perspectives

A final theme that arose during the modeling session was the continual switching of perspectives, from the rules for an individual bacterium to the emergent behavior of its entire colony. The literature on complex systems education suggests that people find it difficult to move in either direction between macro and micro perspectives -- either inferring the emergent result of a micro-level change to a system, or predicting the micro level changes that could cause a given macro-level result [23, 24]. Complex system dynamics are also typically taught only in highly advanced math and science settings. However, the literature also suggests that properly designed activities can help people to grasp complex systems concepts much more easily. The iterative process of modeling that students went through can be seen as a process of writing rules at the level of the individual bacterium in order to create emergent outcomes at the level of the colony. With no prior academic knowledge of agent-based modeling or complex systems, the students in this study managed to describe and manipulate a complex system at both levels, micro and macroscopic. While BM is not inherently bound to a complex-systems framework, the data suggests that the process of modeling a phenomenon was an effective way to intellectually engage students with the dynamics of complex systems.

4.5 Various approaches toward resolving mismatches

Results from these four pilot studies suggest that adjustment in a BM activity would change students' approach toward resolving mismatches between the real and virtual models, within the main goal of evaluating the different implementation models (see Figure 5). In this section, instead on analyzing particular aspects of the bacteria growth study, I change our focus to comparing different implementation models, in order to investigate how the presence of each of the components of a bifocal modeling changes students' engagement and learning. For example, I was interested in finding out how the presence of a longer model building phase would influence how students conducted the model comparison.

In the first study (bacterial growth), I designed the activities so that I mostly had students focused on creating a conceptual agent-based model to match the imagined emergent behaviors to the real time-lapse video data. Students were actively constructing a model on the whiteboard, even though they were *not* writing the code. Overall, the group's method was to "run" a few steps of their whiteboard virtual model in order to see how the bacteria grew, and compare the results to their goal – the growth curve calculated from the physical model. Then, they would resolve the perceived differences between the two by adding rules and variables to the virtual model. In general, as I will discuss in the following paragraphs, I observed that due to the intense model building activity, students in this study were more engaged in investigating the behavior of the phenomenon.

In the second study about the "ball on a ramp" model, I made different design decisions, given the size of the group (11) and the available time (6 hours total). Students partially designed and developed their own physical model, but the virtual model was given to them, so the emphasis was just on interacting with the pre-made virtual model. Interestingly, as students proceeded in the activity, they became more critical about their own observations rather than questioning the pre-made model and its assumptions. For example, in their physical experiment, heavier balls appeared to roll down faster, possibly due to air resistance, slipping, and friction. When the virtual model appeared to refute the idea that heavier balls would roll faster (as they experienced in their physical experiment), students were surprised, and ended up trusting the given computer model more than their own observations. For example when asked about which model would better represent the scientific phenomenon, one student said that it would be "…the virtual model! It is computerized and can calculate the time, it is a computer so we trust it!" In general, students never questioned if the computer model could possibly be wrong, and just assumed that if since they were (supposedly) created by experts, they would be "right."

In the "Gas Laws" study, again, the emphasis was on interacting with pre-made models rather than creating them. In this case, students did not build any of the two models: they were given both a physical and a virtual model. Students were tasked with collecting real-time data from the pressure sensor, and comparing with the "ideal" data generated by the pre-made virtual model. Students critically evaluated the scientific experiment with sensors and offered many ideas about how to improve it, trying to make sense of the discrepancies between the two datasets. For example, when asked about the discrepancies between the P-V graph which resulted from their own physical measurement, compared to the one demonstrated by the virtual model, the causes that students mentioned were the accuracy of the sensor and data-logging software. Again, they never mentioned that the virtual models could have been wrong. For example, when trying to critique their physical model, students only looked for technical issues such as limitations of the sensors, or the limits of compressibility of the air inside the syringe. Again, judging by their utterances during the activity, similarly to the previous study, students did not even consider that the computer models could have been wrong or imperfect. They took their accuracy for granted and simply critiqued their own data, even after having repeated the experience many time with similar results.

In the last study, students had not only to come up with their own idea for a project, but design both the physical and virtual models from scratch. During the construction itself of the physical model, many dissimilarities were foregrounded. For example, one group decided to build a bridge to investigate how much vibration it would withstand, together with the accompanying computer model (Figure 11).

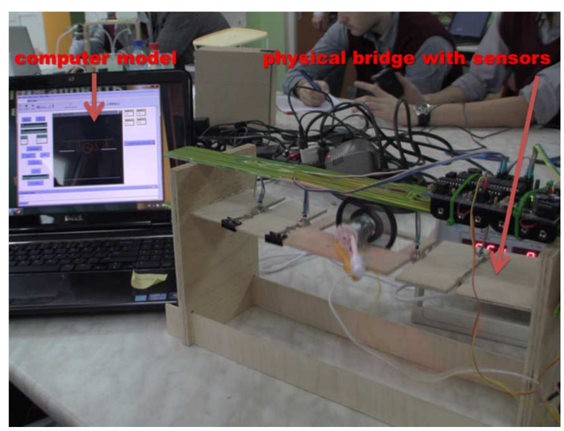

Figure 11: A Bifocal Model for bridge harmonics, with the NetLogo model of a bridge (left), and physical bridge with sensors and a vibrating motor (right).

During the construction of the bridge, the facilitators encouraged students to run systematic experiments with different frequencies of vibration, comparing them with the canonical formula. Even though they were able to construct a plot that approximated the canonical formula, it was evidently not a perfect match since there is intrinsic error in the empirical measures. At first, students felt that their model was wrong since it was not fitting the theoretical curve perfectly – a big disappointment for the group. However, through multiple cycles of measurement and rebuilding the system, students realized that they were always getting "messy" results, and that their initial goal of a perfect fit was not just a matter of "getting it perfect," but an impossibility. They tried to carefully control the voltage source (which controlled the vibration frequency), the location of the sensors, and the magnetic pieces, but finally realized that even after multiple changes to both the computer model and the physical mode they could make the models match.

In this case, I hypothesize that by constructing both the computer and the physical models, and glass boxing the entire process, students had a much more comprehensive set of tools to make sense of the differences and mismatches, as evidenced by the sophistication of their attempts to make both systems match. However, further research needs to be done to evaluate if the extra time invested in learning the programming language and all the digital fabrication machines was advantageous in terms of the further insight into the models and the learning activity.

One last example from this implementation model sheds some light into the usefulness of the full-fledged Bifocal Modeling activity, in which students build both the physical and computer models. A group of three students got interested in building a model to explain how an ice cube would melt (Figure 12). They froze temperature sensors inside an ice cube and placed it on top of a heat source (a toaster oven) and also instrumented it with the same type of sensors. They carefully tracked the temperature of the surface of the heat source and of the ice cube, and carefully examined the two plots to generate a tentative equation and plot relating them (see top right plots in Figure 12). However, after some hours, they realized that their equation was not a mechanistic model of what was happening with the ice cube – it was merely a descriptive relationship. Even after several refinements, the students were unease about their project because they wanted to dive deeper into the mechanism of melting and really understand why the ice was melting, and not only how fast it was happening. They embarked then in a much more ambitious project: create a NetLogo model to describe what was happening microscopically "inside" the ice cube. They programmed an atomic-level agent-based model (see bottom right of Figure 12) in which the atoms were connected by springs and allowed to vibrate and eventually break off, and "heat waves" (represented by small triangles at the bottom) would collide with the atoms and increase their vibrational energy. Therefore, students arrived at a remarkably complex and accurate mechanistic model of melting by going through several iterations of model building and comparison. Ultimately, they realized that the equations they were given at school (which they were using as a reference pattern for the initial part of their project) were not exposing the mechanism of the phenomenon, which was ultimately their goal for the project. The Bifocal Modeling activity, I hypothesize, gave them the technological tools and activities that highlighted imperfections in the models, and led them to increasingly complex endeavors: their goal went from generating hypotheses about "blackboxed" numerical relationships to deep insight into mechanisms behind them.

Figure 12: A Bifocal Model for a melting ice cube. The kitchen oven melts the ice (left), and NetLogo both models the phenomena from a differential equations perspective (top right) and agent-based perspective (bottom right).

6. CONCLUSION

Our goal in this paper was to offer initial data on the comparison of many different implementation models for Bifocal Modeling. The first study was a proof of concept that established the feasibility and some of the learning gains of students engaging in Bifocal Modeling. Next, I intended to compare several models of implementation of BM. From the four studies, I observed at least one overall pattern across different implementations: resources that are given to students have a different perceived value compared to the ones that are constructed by the student. "Given" resources are always trusted more. Thus, the only way for a constructed resource to achieve the same validity as a given one would be for it to perfectly match the latter. Therefore, it seems like this asymmetry could be counterproductive for students, especially when the given model is the theoretical model.

A second pattern was that in the studies in which there was no virtual model-building (gas laws and ball/ramp), students' level of sophistication in comparing real and virtual models was lower, and their epistemological stance was even more radical: they would critique their work and their own observations but rarely question the computational models that were given to them.

I also observed that the benefits of model-building appear even if students are not coding, but creating "paper models" models, but only if they use the paper or the whiteboard as a 'computational surface' that can enact the imagined agent-rules. Within this context, the use of the physical model as a reference pattern for the creation and refinement of the virtual model was generally effective. When students were instructed to design a virtual model that recreated the bacterial growth curve, they used their previously-learned knowledge about the curve and the physical appearance of the bacteria as a reference patterns for what their model should generate. When the model data did not match the observed data, they went back and made changes.

One key conclusion from these four implementations is that the full model building experience (both physical and virtual) was indeed a richer learning experience, especially considering students who build several versions and types of computer models. However, with the proper facilitation and a careful choice of which modeling phase to abbreviate (e.g., bacteria study), relatively rich learning outcomes can be achieved in a dramatically reduced time-frame. *However, these studies have shown that model-building, rather than simply having access to* *sensors and tangible learning tools, was the determinant factor in generating deep engagement with the phenomenon.* Further research is needed to determine the degree to which model building can be abbreviated without significant decrease in learning gains and engagement.

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