Providing Guidance and Opportunities for Self-Assessment and Transfer in a Simulation Environment for Discovery Learning

Jason Tan[1], Nathan Skirvin[1], Gautam Biswas[1], Kefyn Catley[2]
{jason.tan, nathan.skirvin, gautam.biswas, kefyn.catley }@vanderbilt.edu
[1]Department of EECS / ISIS, Vanderbilt University
[2]Department of Teaching and Learning, Vanderbilt University
Nashville, TN 37235 USA

Abstract

This paper describes the use of a computer-based simulation learning environment to teach fifth grade students about dynamic processes in a river ecosystem using guided discovery learning techniques. The simulation is framed in an established learning-by-teaching environment called Betty's Brain, where students create causal concept maps to understand interdependence and balance. Students were asked to manipulate and observe the simulation and teach the computer agent, Betty, using the knowledge acquired from the simulation. We present the design of the simulation environment and the implementation of its components: the simulation engine, the display and control interface, tools for guided discovery learning, and the self-assessment subsystem. A study was run on two classrooms to examine the effectiveness of the system. Student understanding was measured by pre to post test differences. Students using the system showed significant learning gains in important concepts. We also studied student learning behaviors in the simulation environment, and found that those who better utilized the self-assessment system performed better on the post test.

Keywords: simulations, scientific discovery learning, self-assessment, transfer, learning by teaching

Introduction

Constructivist approaches to education involve experiences through observation, exploration, and performance (Dewey, 1938). Tools provided as scaffolds can support learners in constructing their own knowledge with less frustration, more motivation, and more efficiency and innovation in the learning process. These tools can enhance activity and thinking (Vygotsky, 1978). Computers have become a versatile tool through which one can gain a wide variety of learning experiences. In particular, the integration of simulation, graphics, and animation enables users to experience and witness processes that might not otherwise be readily observable and comprehendible. This makes computer-based simulations a powerful tool for learning.

In simulation-based learning environments "the main task for the learner is to infer the characteristics of the model underlying the simulation" (de Jong and van Joolingen, 1998). In other words, the simulation environment provides learners with observations and experiences that they must attempt to explain, assimilate, and combine with their existing knowledge. One way to do this is to provide scaffolds and guidance that help users generate hypotheses, use interactive controls to manipulate the simulation, run experiments and verify the hypotheses, and then apply the learnt knowledge to answer questions and solve problems in different situations. Researchers have confirmed that "exploratory learning" with understanding and the ability to transfer in learning environments can lead to "effective learning" (Schwartz and Bransford, 2005).

In our work on middle school science education, we have been developing a teachable agent environment called Betty's Brain, where students teach the computer agent, Betty, by creating concept maps. The concept map representation and reasoning mechanisms are geared towards teaching and learning about *interdependence* among entities in river ecosystems. Analysis of student answers to post-test questions on *balance* (*equilibrium*) made it clear that students did not quite grasp this concept and how it applied to river ecosystems. We realized that to understand balance, students had to be introduced to the dynamic behavior of river ecosystems.

Analyzing dynamic systems behavior can be very challenging for middle school students who do not have the relevant mathematical background or the maturity to grasp these concepts. To scaffold the process of learning about temporal effects, we have developed a simulation-based learning environment that supports scientific discovery learning in the domain of river ecosystems. This support comes in the form of guidance, scaffolding, and mechanisms for self-assessment and transfer. The addition of a simulation environment allows students to explore and conduct experiments about dynamic processes in the ecosystem.

Scientific Discovery Learning

Scientific discovery learning environments provide the learner with resources and tools that help them deduce properties of a specific domain by running controlled experiments or by accessing relevant data that is made available in the environment (van Joolingen and de Jong, 1997). They promote a constructivist form of learning where students start with a science problem, formulate hypotheses, design experiments, and then discover the relations needed to solve the problem. The learning environment may include additional resources and tools to help students focus on the primary entities and relations that are important to the discovery learning process (de Jong and van Joolingen, 1998).

Simulations can form the core of scientific discovery learning. They represent models of the underlying phenomena or domain of study (Wilensky, 2006). The primary task for the student is to run experiments with the simulation and inspect the observed behaviors to discover the model or

parts of the model. The experiments require setting simulation parameters within allowable ranges, and using the behaviors generated for testing different operating conditions. Researchers believe that this approach has great potential for education (Sandoval and Reiser, 2003).

de Jong and van Joolingen (1998) conducted a survey of pedagogical simulations and identified several common impediments to their effective use. This included: (i) *hypothesis generation*, where students had difficulty successfully forming and understanding what a hypothesis is, and failed to adapt their hypotheses to available data; (ii) *design of experiments*, where students created experiments that had no relationship with the variables of the hypothesis, or modified too many variables, which produced useless or incomprehensible results; and (iii) *interpretation of data*, where students had trouble finding regularities in data or interpreting the meaning of data supporting the hypothesis. Moreover, being novices in scientific reasoning, students tended to force the data to fit their pre-conceptions and misconceptions. In some situations the lack of a problem solving context often hindered students from self-assessing and evaluating their own learning as they worked in the simulation environment.

Designing Simulation Environments for Learning about Dynamic Processes

The goal of a simulation-based learning environment is to promote deep learning where students not only learn direct relations between observed variables, but develop an understanding that allows them to transfer this knowledge to other problem-solving situations. Deep learning requires the ability to understand, interpret, and reason with the underlying model of the dynamic processes that govern the simulation (Biswas, et al., 2005). To address the difficulties of scientific discovery learning in simulation environments discussed in the last section, and to ensure that students can apply their learnt knowledge to problem solving tasks, we developed four primary design goals.

Guided Exploration

Learning of complex phenomena involves iterative cycles of goal setting, planning, executing, and assessment (White, 1999). For scientific discovery learning, this translates to cycles of hypothesis generation, design of experiments, and interpretation of data. Simulation environments must provide resources and tools that guide learners through conducting experiments. The learner should be free to explore but the learning environment should guide the user towards those experiments which reveal the important aspects of the "inspectable" model.

Scaffolding

Scaffolding provides a framework for exploration in a meaningful context. Scaffolding must also provide tools and resources to aid students with tasks that are currently be-

yond their capabilities. The tools should also assist learners in interpreting data generated by the simulation.

Self-Assessment

Effective learning requires learners to have the ability to assess their learning, receive feedback, and revise their learning process (Bransford, 2000). Assessment should occur not only after, but during the learning process. A simulation environment should include methods for formative assessment, which allow learners to monitor their learning and enable them to correct their mistakes and misconceptions. Self-assessment mechanisms can assist learners in developing metacognitive skills.

Transfer

The transfer of acquired knowledge into other representations and problem solving situations promotes deep learning (Bransford and Schwartz, 1998). This is particularly important in a simulation learning environment, where the learner has to understand the underlying rules of the simulation model. If the learning environment helps the student to apply this to other problems, students will have the opportunity to explicitly think about and encode these rules, rather than merely observing the rules in action.

Implementing the Simulation-Based Learning Environment

In this section, we describe the implementation of a simulation-based learning environment called *Ranger Joe* based on the design goals listed above.

Figure 1: The Ranger Joe environment

Guided Exploration and Self Assessment

Ranger Joe features the *Challenge Zone*, which guides the learner's interaction with the simulation. It provides important background information to help students generate relevant hypotheses and suggestions for setting up and running experiments. The Challenge Zone poses a series of questions to help focus student learning. The questions may direct students to run the simulation under specific conditions and compute specific parameter values or infer relations between entities to interpret the results of the simulation.

Students' scores are based upon the number of attempts they need to correctly answer a Challenge Zone question. This gives the students the opportunity to assess their understanding of the simulation, and do it by understanding the phenomena rather than just guessing an answer.
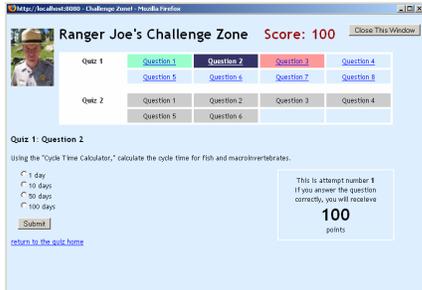

Figure 2: The Challenge Zone

Scaffolding

The Ranger Joe environment also provides a set of *tools* that help facilitate the understanding of dynamic processes in terms of two parameters: the baseline value and cycle time. The *baseline calculator* helps students compute the average value of a time-varying behavior by collecting information from multiple situations. The *cycle time calculator* helps students compute the average cycle time (rate of change) by noting the occurrence of a sequence of peaks and valleys.

Students are also presented with hypertext resources that provide supplemental information about the river ecosystem and simulation. These support tools provide information about questions posed in the Challenge Zone.

Transfer

In order to provide a mechanism for students to transfer the knowledge they learned from the simulation into another representation, the simulation environment is linked to *Betty's Brain*. The interface to the system is illustrated in Figure 3. The teaching process is implemented as three primary components: (i) *teach:* Students explicitly teach Betty using a concept map representation, (ii) *query:* Students use a template to generate questions to see how much Betty has understood, and (iii) *quiz:* Students send Betty to take a quiz and observe her performance on a set of predefined questions. Once taught, Betty uses qualitative reasoning methods to reason through chains of links (Forbus 1984; Biswas, et al. 2005) to answer questions, and, if asked, explain her reasoning using text and animation schemes. Betty also provides feedback on students' teaching behaviors to help students develop metacognitive strategies (Tan, Biswas, and Schwartz 2006).

Detailed descriptions of Betty's Brain and the results of several studies run with fifth-grade students are described elsewhere (Tan, Biswas, and Schwartz 2006). While the ideas of interdependence and causal chains were taught by the previous versions of Betty's Brain, dynamic and temporal ideas were not. It may be the case that an entity decreases, affects other entities, which then cycle back to the original entity. A new, temporal version of Betty's Brain incorporates reasoning mechanisms for such cycles of behavior. Users specify cycles as they teach Betty and include information about time.
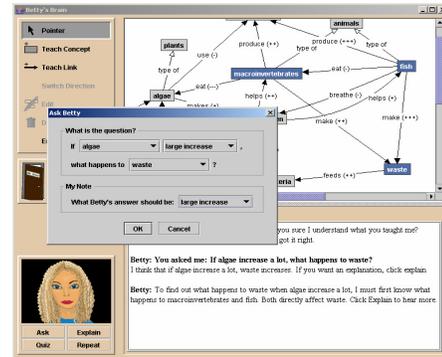

Figure 3. Betty's Brain

Implementing the Simulation Model

The interacting entities in an ecosystem are typically modeled as differential equations or discrete time state space models. However, this type of model is better suited for expert analysis rather than as a simulation model for a learning environment. In order to create a simulation model with underlying rules that can be inspected through exploration, we have employed a multi-agent approach using NetLogo. NetLogo is a modeling environment well suited for simulating complex systems using the emergent behavior of independent agents (Wilensky 1999). It provides a robust multi-agent programming language and the ability to generate visual representations of the simulated environment and graphs of the included entities.

This approach accurately reflects the ecological system by modeling each entity (fish, algae, macroinvertebrates, etc.) in the river as an agent. Rules associated with each type of agent are executed at each time step during the simulation. These agent-specific rules can be relatively simple but still capture the complexities of a dynamic system. When all of the agents interact with one another in an environment, the sum total of their behaviors defines the visible behavior of the real-world system.

Some of the agent actions are randomized (e.g., fish movement) or they occur with a certain probability (e.g., macroinvertebrate reproduction). Since the simulation is stochastic, every simulation run may provide a slightly different result quantitatively, even when the simulation parameters are unchanged. This reflects what would happen in a real world environment. Students quickly realize that they may need to run the simulation several times and make multiple measurements or take measurements at several points to compute average behaviors or derive qualitative relations that correctly define expected parameter values and relations between entities. This is an important lesson they learn about scientific experimentation, hypothesis generation, and verification while working in this environment.

The River Ecosystem Models

Two models are developed for this simulation. The first models the fish-macroinvertebrates cycle. The second models a more complex system by including algae, dissolved oxygen, and dissolved carbon dioxide. By breaking the system dynamics into multiple cycles, the students might progressively learn the relationships that produce the dynamic cyclic behavior (balance), and not be overwhelmed by the complexity of the model.

The fish-macroinvertebrates cycle is a simple predator/prey model, in which one species consumes the other. A very clear cyclical behavior emerges, where the decrease in one entity results in the increase in the other, until some minimum or maximum threshold is reached and the growth is reversed. In the second model, algae and macroinvertebrates form a second predator/prey cycle.

The idea of *balance* is inherent in this system. Should an extreme amount of either entity exist, the system will go out of balance, resulting in a deviation from the regular, cyclical growth behavior.

Experimental Design

46 students from two fifth-grade classrooms participated in the study. The students were given a pre test which contained questions on concepts such as balance, causality, chains of events, and reading and interpreting graphs. Students were given five 50-minute sessions to work with the Betty's Brain/ Ranger Joe system each day. Each student was required to go through two iterations of teaching Betty, using the simulation, and going back to teach Betty temporal information learned from the simulation. A week after using this system, the students were given a post test. The post test contained the same questions as the pre test along with 5 additional questions related to reasoning with a concept map containing cycles. Analysis of the pre and post tests would determine if the system improved students' understanding of balance and dynamic processes.

In the first iteration, students teach Betty about fish and macroinvertebrates. The relationships between the entities at this point are direct relationships with no temporal information. Betty must pass a quiz which asks questions about how fish and macroinvertebrates are related. After successfully getting Betty to pass the first quiz, the student is prompted to visit Ranger Joe.

In the students' first visit to Ranger Joe, the simulation only displays fish and macroinvertebrates. The students are guided through the simulation environment by the Challenge Zone questions and hypertext resources. After using the simulation to answer all of the Challenge Zone questions correctly, the students return to Betty and add temporal information to the concept map to teach Betty about the fish and macroinvertebrate cycle. Betty must again pass a quiz, but this time, the questions involve temporal information.

In the second iteration, students add the concepts of oxygen, carbon dioxide, and algae to the concept map. Again, Betty must pass a non-temporal quiz containing information on these concepts. Students then return to Ranger Joe,

where they are presented with a fuller simulation including the additional elements of dissolved gases (oxygen and carbon dioxide) and algae. After answering a new set of Challenge Zone questions, students return to teach Betty about the additional cycle. Students have completed the entire task when Betty passes the final temporal quiz.

Results

The pre and post tests consisted of 3 free response questions (Q1-Q3) and 7 multiple choice questions (Q4-Q10). In previous studies, students using Betty's Brain showed significant improvement on post test questions that required understanding the concept of interdependence (Leelawong, 2005). However, they did not show significant improvement in understanding the concept of balance in an ecosystem. The 3 free response questions on the pre and post tests for this study focused on gauging students' understanding of balance. An example of these questions is, "Explain in your own words what it means for a river to be in "balance." These free response questions carried a maximum value of 6 points each. The multiple choice questions were directed at extracting information from graphs. Students' answers were scored as either right or wrong (1 or 0 points). Students were also given 5 additional questions on the post test which involved reasoning with a cyclical graph (similar to the concept map representation they used to teach Betty). An example of one of these questions is, "If the amount of fish increases, what would happen to the number of macroinvertebrates after 10 days?" These were questions Q11-Q15. All of the non-multiple-choice questions were hand-graded by two coders according to a pre-defined rubric.

The table below presents the results of paired t-tests which determine if there was a significant increase from pre to post test scores across all students. The mean pre test score and post test score are reported for each category of questions. We did not look at the total score because an aggregated value of both free response and multiple choice questions would require a scaling of how much each type of questions is worth in relation to the other.

Table 1: Paired t-test results for pre to post test scores (n=46, df=45)

	Pre (std dev)	Post (std dev)	t	Sig (1-tailed)
Free response	9.26 (3.87)	11.50 (3.48)	4.020	< 0.001
Multiple choice	4.41 (1.34)	5.04 (1.41)	2.655	0.006

There was a highly significant improvement from pre to post on the free response questions ($p<0.001$) and a significant improvement on the multiple choice questions ($p<0.01$).

Table 2 presents the results of additional paired t-tests determining which questions had significant increases from pre to post test. (For the multiple choice questions Q4-Q10, the mean represents the percentage of students answering correctly).

Table 2: Paired t-test results for individual questions with significant pre to post test differences (n=46, df=45)

	Pre (std dev)	Post (std dev)	t	Sig (1-tailed)
Q1	2.93 (2.3)	3.72 (2.13)	2.299	0.013
Q3	2.61 (1.86)	3.74 (1.88)	3.644	0.001
Q5	0.70 (0.47)	0.85 (0.36)	1.855	0.035
Q6	0.46 (0.50)	0.65 (0.48)	2.280	0.014
Q9	0.24 (0.43)	0.41 (0.50)	2.070	0.022
Q10	0.46 (0.50)	0.63 (0.49)	1.834	0.037

When looked at individually, the two questions that showed the most improvement from pre to post were questions 1 ($p<0.05$) and 3 ($p<0.005$). These were both free response questions that dealt with the concept of balance. Students also showed significant improvement on multiple choice questions 5, 6, 9, and 10 ($p<0.05$). Many of the other multiple choice showed no significant improvement due to a ceiling effect.

In addition to the pre to post test score differences, we looked at the students' usage of the Ranger Joe Challenge Zone self-assessment questions. We hypothesized that students using the self-assessment mechanism more effectively would have been able to learn more from the simulation environment and therefore, perform better on the post test.

Table 3: Pearson correlation results between Challenge Zone score and post test score

	Pearson correlation	Sig (1-tailed)
Free response	0.163	0.139
Multiple choice	0.207	0.083
Cyclical graph reasoning	0.414	0.004

There was a significant positive correlation between the Challenge Zone score and the five extra post test questions ($p<0.005$). However, there was no significant correlation between the Challenge Zone score and the free response questions or the multiple choice questions.

The next table lists the individual questions that showed a positive correlation between students' Challenge Zone score and that individual post test question score.

Table 4: Pearson correlation results between Challenge Zone score and individual post test question scores

	Pearson correlation	Sig (1-tailed)
Q2	0.285	0.027
Q3	0.284	0.028
Q6	0.384	0.004
Q7	0.340	0.010
Q8	0.274	0.033
Q13	0.257	0.042
Q14	0.374	0.005
Q15	0.352	0.008

Free response questions 2 and 3; multiple choice questions 6, 7, and 8; and cyclical graph reasoning questions 13,

14, and 15 all showed a positive correlation with the Challenge Zone score. Questions 6, 7, 14, and 15 were highly significant at the $p<0.01$ level. The others were significant at the $p<0.05$ level.

Finally, we wanted to see how the students' usage of the self-assessment questions correlated with their behaviors in Betty's Brain. Three actions: quiz request, query, and resource access where analyzed and their correlations with the Challenge Zone score are listed below in Table 5.

Table 5: Pearson correlation results between Challenge Zone score and frequency of activities in Betty's Brain

	Pearson correlation	Sig (1-tailed)
Quiz requests	-0.198	0.080
Queries	-0.170	0.115
Resource Accesses	-0.194	0.085

Discussion

By using the simulation environment and teaching Betty, students showed significant gains from pre to post test. Use of the system improved their performance overall on both the free response and the multiple choice questions (Table 1). Students showed the most improvement on Q1 and Q3 (Table 2). These questions show that students were able to better understand and explain a chain of events leading to a system going out of balance over time. Students who used Betty without the Ranger Joe simulation system did not exhibit this understanding (Leelawaong, 2005).

Almost all of the questions without a significant increase from pre to post did not show this gain because of a ceiling effect. These questions dealt primarily with reading information from a graph, which shows that the 5th graders were quite conversant in using graphs.

The use of the Challenge Zone self-assessment mechanism in the simulation environment varied. Some students used the questions to carefully conduct experiments in the simulation and find answers. These students received higher Challenge Zone scores because they tended to get the answer correct on the first or second try. Others did not see the value in self-assessment, and tried to guess on some of the more difficult questions. These students received lower Challenge Zone scores because it took multiple attempts for them to get the answers right. Students who did well on the Challenge Zone tended to score higher on the cyclical graph reasoning questions (see Table 3). In particular, those who utilized the self-assessment mechanism more effectively were able to reason with multiple cycles over longer periods of time on Q13, Q14, and Q15 (see Table 4).

Finally, we wanted to see how well students were able to transfer the knowledge they learned from the simulation into another representation. The students' use of the simulation environment should have an effect on their performance in Betty's Brain. In past studies with Betty's Brain, we have looked at the students' concept map quality, behavior patterns, and their ability to construct similar concept maps in other domains (Biswas, 2005; Tan, 2006). Because most of

the students had similarly complete concept maps at the end of the study, the concept maps were not graded. We were able to look at some of the behavioral data as it related to the students' use of the simulation environment and Challenge Zone self-assessment (see Table 5).

Students use the quiz request action in Betty's Brain to get Betty to take a quiz. We have found in previous studies that better students use the quiz request function less (Tan, 2006). It is more effective to spend time carefully constructing and debugging the concept map than to repeatedly ask Betty to take the quiz after each small edit to the map. Students who are less successful in teaching Betty revert to this trial-and-error pattern. Quiz requests were slightly negatively correlated (at $p<0.10$ level) with the Challenge Zone score. This suggests that the students who used the simulation more effectively were able to successfully teach Betty with less quiz attempts.

When teaching Betty, students have access to a set of hypertext resources which provide domain knowledge to assist the student with constructing a correct concept map. Resource accesses were slightly negatively correlated (at $p<0.10$ level) with the Challenge Zone score, suggesting that students who used the simulation more effectively did not need to access the resources as much in order to construct the concept map representation. This may be because they learned more from the simulation environment than the other students.

Further analysis on the students' behavior and performance in Betty's Brain needs to be completed in order to better understand how well the students were able to encode the model they learned from the simulation into the representation used to teach Betty.

Conclusions

Our simulation-based learning environment provides students with guidance for scientific discovery learning, and opportunities for self-assessment and transfer as they learned about river ecosystems. Students using the learning environment showed significant improvement from pre to post test on important topics and demonstrated understanding of dynamic processes and balance in an ecosystem. Although all of the students used the same learning environment, we were able to evaluate the role of self-assessment by studying the students' Challenge Zone use and correlating self-assessment with learning gains. We found that students who were better at assessing their own learning were able to perform better on the post test. Additionally, they seemed to be better equipped to transfer what they learned into another representation.

Our use of simulations suggests that when embedded in a well-designed learning environment, they can be a useful tool for scientific discovery learning. Based on these findings, we plan to improve on our current system and run a more in-depth study which further investigates the students' ability to transfer knowledge learned in the simulation.

References

Biswas, G., Schwartz, D., Leelawong, K., Vye, N., and TAG-V (2005). Learning by teaching: A new agent paradigm for educational software, *Applied Artificial Intelligence*, special issue on Educational Agents, 19(3), 363-392.

Bransford, J.D. & Schwartz, D.L. (1999). Rethinking transfer: A simple proposal with multiple implications. *Review of Research in Education*, vol. 24, pp. 61-101.

Bransford, J.D., Brown, A.L., et al., Eds. (2000). *How People Learn*. Washington, D.C., National Academy Press.

Forbus, K. (1984), Qualitative Process Theory, *Artificial Intelligence*, 24.

de Jong, T., & van Joolingen, W. R. (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research*. 68(2): 179-201.

van Joolingen, W. R., & de Jong, T. (1997). An extended dual search space model of scientific discovery. Ins*tructional Science*, 25, 307-346.

Leelawong, K. (2005). Using the Learning-by-Teaching Paradigm to Design Learning Environments. Ph.D. Thesis. Department of EECS, Vanderbilt University, Nashville, TN.

Sandoval, W. A., & Reiser, B. J. (2003). Explanation-driven inquiry: Integrating conceptual and epistemic scaffolds for scientific inquiry. *Sci Ed*, *88*, 345-372.

Schwartz, D.L. Bransford, J.D. & Sears, D.L. (2005). Efficiency and innovation in transfer. J. Mestre (Ed.), *Transfer of learning from a modern multidisciplinary perspective* (pp. 1 - 51). CT: Information Age Publishing.

Tan, J., Biswas, G., and Schwartz, D. (2006), Feedback for metacognitive support in learning by teaching environments. The 28th Annual Meeting of the Cognitive Science Society, Vancouver, Canada, 828-833.

Vygotsky, L.S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.

White, B., Shimoda, T., and Frederiksen, J. (1999). Enabling students to construct theories of collaborative inquiry and reflective learning: Computer support for metacognitive development. *International Journal of Artificial Intelligence in Education*, vol. 10, pp. 151-182.

Wilensky, U. (1999). "NetLogo" [Computer software]. Evanston, IL: Northwestern University, Center for Connected Learning and Computer-Based Modeling,.

Wilensky, U. & Reisman, K. (2006). Thinking like a wolf, a sheep or a firefly: Learning biology through constructing and testing computational theories - An embodied modeling approach. *Cognition & Instruction*, 24(2), 171-209.