Promoting Learning in Complex Systems: Effect of Question Prompts versus System Dynamics Model Progressions as a Cognitive-Regulation Scaffold in a Simulation-Based Inquiry-Learning Environment

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Abstract: Designing effective technology-based learning environments is challenging. Designing effective technology-based learning environments to facilitate learning about complex knowledge domains is more challenging. To a large extent, the key to the puzzle lies in identifying which scaffolding strategies are more effective; and under which conditions. In a simulation-based inquiry-learning environment, this controlled study investigated the effect of two promising scaffolding strategies; *question prompts* and *system dynamics model progressions*, on ninth-grade biology students' cognitive regulation and complex problem-solving skills. For simpler complex problems, findings suggested that both scaffolding strategies were equally effective. However, as the problems increased in complexity, system dynamics model progressions were significantly more effective for facilitating both cognitive regulation and complex problem-solving skills.

Introduction

How can we effectively facilitate learning in complex knowledge domains such as science, technology, engineering, and mathematics (STEM)? This question led us to the study presented in this paper. Recent research on problem solving in complex knowledge domains illuminates a number of learning challenges due to the nature and structure of the real-life problems in these domains. For instance, ecology is a difficult subject matter for many students. Learning ecology calls for learning about the complex ecology systems. In other words, students should understand the dynamic interdependencies among different organisms and their environment. As such, a complex system involves a large number of interdependent variables and they are all connected with one another dynamically (Dörner, 1996). Prior research suggests that humans have significant difficulties in understanding complex systems, due to the challenges involved in building a mental representation of complex systems, predicting dynamics outcomes, monitoring the cause and effects of complex systems, and monitoring their own strategies of information processing. (Dörner, 1996; Dörner & Wearing, 1995; Funke, 1991).

Mental model theory provides a framework to understand the learning processes of complex systems, in which learners take the input from their learning environments and simulate the events in their mind to accommodate revised mental models (Rumel, Smolensky, McClelland & Hinton, 1986; Seel, 2001). While learning about complex systems, learners are required to construct and reconstruct their mental models, which (1) guide learners' comprehension of the systems, (2) allow them to explain the system states, and (3) allow them to predict the system behaviors (Greeno, 1989; Seel, 2006; Young, 1983).

Therefore, it is argued that simulation-based inquiry learning environments would help students in the inquiry processes, because they allow learners to visualize and investigate complex systems (de Jong & van Joolingen, 1998; Linn, Davis & Bell, 2004). In a simulated-based inquiry-learning environment, students are expected to discover dynamic relationships underlying a complex system through an iterative process of hypothesis generation, data collection, and data analysis. Indeed, simulation-based inquiry learning is gaining visibility, especially in the area of science education, as a way to address the challenges of complex learning (The National Research Council, 2000). Education researchers advocate simulation-based learning environments to foster scientific inquiry skills (Wilensky & Reisman, 2006). However, studies showed that many students have difficulties with simulation-based inquiry learning (Hogan & Thomas, 2001). In addition, the effectiveness of inquiry-based learning is debatable (de Jong & van Joolingen, 1998; Linn et al., 2004). Recent research suggests that low-level cognitive regulation skills are a major cause of failure in simulation-based inquiry learning (Lavioe & Good, 1998; Simmons & Lunetta, 1993; Schauble et al., 1991; Shute & Glaser, 1990).

Cognitive regulation, which refers to how individuals engage in a recursive process utilizing feedback mechanisms to direct and adjust their learning and problem-solving processes, is crucial for constructing mental model of the complex system to be learned (Azevedo, Guthrie & Seibert, 2004; Manlove, Lazonder & de Jong, 2006), especially when learners are lacking required domain knowledge (Pintrich, 2000). Thus, it is argued that simulation-based inquiry learning environments should include scaffolds to support students' cognitive regulation. This, in turn, would positively support students' inquiry processes starting from hypothesis generation to their interpretation of the findings.

A review of the literature reveals two quite different scaffolding strategies for cognitive regulation that can be ubiquitously embedded into simulation-based inquiry learning environments: (1) question prompts (Ge & Land, 2004); and (2) model progressions (White & Frederiksen, 1990). Providing question prompts to students yielded promising results in some studies (see Ge & Land, 2003); however, others did not yield such positive results (see Greene & Land, 2000; King, 1992). Similarly, model progression did not yield consistent effects on learning performance (Alessi, 1995; Quinn and Alessi, 1994; Rieber and Parmley, 1995). We argue that questions prompts and model progressions may enhance students' cognitive regulation skills, which, in turn, foster their learning of complex system; however, the complexity of the learning domain is a main factor determining the effectiveness of question prompts and model progressions as cognitive regulation scaffolds.

Despite its importance, however, there have been very few systematic studies on which of these strategies are more effective, under which conditions, in scaffolding students' cognitive regulation and learning about complex systems in a simulation-based inquiry-learning environment (Kirschner, Sweller, & Clark, 2006). Moreover, limited number of studies investigated the relationships between cognitive regulation and learning performance in complex systems while existing studies on other technology-based learning environments point out to mixed results.

The purpose of this study is to examine the effect of two promising technology mediated scaffolding strategies, *question prompts* and *model progression*, on ninth-grade students' cognitive regulation skill acquisition and learning about complex ecology systems. We hypothesize that task complexity is an important determinant for whether or not certain cognitive regulation scaffolding strategies are effective. This study seeks to replicate past findings and eliminate some confounding factors.

The reminder of our paper is organized as follows. The next section presents the details of the research study, the research questions, the design of the experiment and the data analysis methods. Then, results are presented. Finally, we conclude with a discussion of the implications of our study and provide suggestions for future research.

The Present Study

The purpose of this study was to investigate the effects of (1) *question prompts (QP),* and (2) *system dynamics model progressions (MP)*, in scaffolding ninth-grade students' learning of a complex ecology system in a simulation-based inquiry-learning environment. In addition, this study aimed at examining the relationships between cognitive regulation, learning about complex systems, and task complexity. Thus, the following research questions were posed:

1. Does scaffolding with question prompts and system dynamics model progressions affect students' cognitive regulation in the process of developing solutions to problem scenarios ranging in their level of complexity?
2. How do task complexity influence the effectiveness of question prompts and system dynamic model progressions as cognitive regulation scaffolds to support students' learning about complex ecology system?

Participants and Design

A rural high school in the Midwest of the United States was used as a testbed for this study. 251 ninth-grade biology students were randomly assigned to one of the ten classes. Out of these ten classes, five were randomly assigned to experimental (system dynamics model progression group) condition and five were randomly assigned to control (question prompts group) condition. Of the 219 students, from whom we received both consent and parental assent forms, 113 were in the experimental group and 106 were in the control group. There were 50.6% males and 49.4% females.

Materials

Food Chain is a simulation-based inquiry-learning environment designed to support students while they carry out a sequence of activities that correspond to the steps in the scientific method. *Food Chain* incorporated always-available domain-specific knowledge, scaffolded activities, and analytic tools to help students learn about the processes of experimental design and data analysis, the nature of scientific argument and proof. Scaffolding strategies incorporated in *Food Chain* are aimed at supporting cognitive regulation, metacognitive, and inquiry skills required for implementing scientific methods and effective complex problem-solving. *Food Chain* was originally developed by isee Systems and modified for the purposes of this study.

Procedure

Participants in both study conditions interacted with the *Food Chain* simulation-based inquiry-learning environment for three weeks. In the first week, participants were introduced to the *Food Chain* simulation-based inquiry-learning system. They were asked to design their own experiments and test their hypotheses to answer a relatively simple complex problem (challenge# 1): which two species (out of eight) can survive in Lake

Mirabile by themselves for 90 days? This first week was intended to familiarize students with the simulation environment and to teach about scientific reasoning processes of hypothesis generation and testing. During this initial run, students in both conditions had access to domain-specific knowledge related to the species in Lake Mirabile, but they did not receive any scaffolding from the system. At the end of each inquiry-cycle, they only received a text-based verification feedback of whether or not their hypotheses were correct.

In the second week, participants tackled a problem scenario with medium complexity (challenge# 2), in which they were asked to identify the smallest number of species that will enable Sunfish, one specie out of the eight species in the simulated environment, to survive for 90 days in Lake Mirabile. Their entire hypotheses, experimental designs, and elaborated reports of the findings were collected.

During the third week, participants tackled a very complex and ill-structured problem scenario (challenge# 3), which called for environmental policy-making. In this problem scenario, students were asked to play the role of an environmental scientist and evaluate the proposal to build 100 new houses on the shoreline at Lake Mirabile from an environmental impact standpoint. All of their hypothesis, results of their experiments, and their elaborated report of recommendations and assessment were collected.

During the second and third weeks, the only difference between the two study conditions was the type of scaffolding strategy provided by *Food Chain* at the end of each inquiry cycle. Following their experiment, participants in the experimental (MP) condition were only provided with a text-based verification feedback (e.g., Nice try…but the species you chose didn't survive! View logic model and try again) and they were given access to the system dynamic model progression, which included an annotated system dynamics model progression (see Figure 1). On the other hand, participants in the control (QP) condition were only provided with a text-based verification feedback and related question-prompts (see Figure 2) to scaffold their new hypothesis generation.

Measures and Data Analysis

In *Food Chain*, students were required to go through inquiry processes to solve three ecology problems in increasing complexity. For each problem, they were asked to go through the inquiry process at least four times. Each inquiry cycle in *Food Chain* simulation involved the following steps. First, students individually developed a hypothesis using their prior knowledge and information given by the software. Then, they observed the results and analyzed the charts generated by the simulation environment for each variable. Finally, they explained the results. A computer-generated question prompt or an annotated dynamic model progression was provided to the students to interpret their findings. Students were expected to develop their subsequent hypotheses using these scaffolds. Scoring rubrics were used to rate participants' *cognitive regulation* and *complex learning* based on their protocols, which included, for each challenge (complex problem) in the *Food Chain* simulation, four sets of hypotheses, hypotheses justification, results, and explanation of the results.

Cognitive regulation refers to how individuals engage in a recursive process utilizing feedback mechanisms to direct and adjust their learning and problem-solving activities. Therefore, *cognitive regulation* was measured by rating how well the previous inquiry cycle informed the consecutive inquiry cycle, and whether or not the participant responded the cognitive regulation scaffold (question prompt or system model) in generating and justifying the subsequent hypothesis (see Table 1).

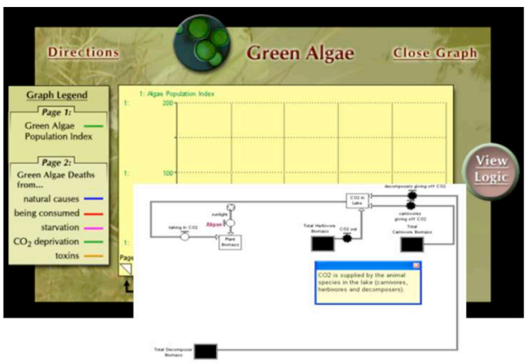

Figure 1. Model progression scaffold received by participants in experiment condition

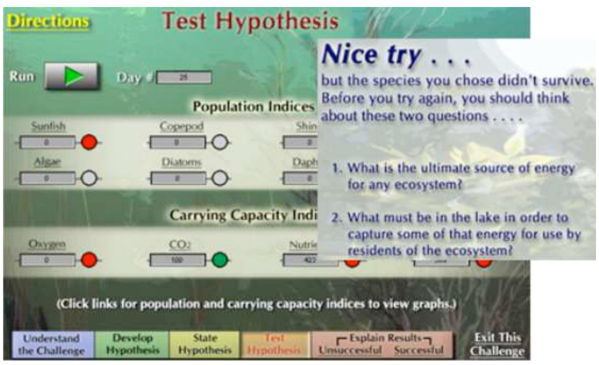

Figure 2. Model progression scaffold received by participants in experiment condition

Table 1: Overview of the scoring rubric for *cognitive regulation* measure

Coding Category	Number of points given
Quality of the hypothesis	2 points: strong evidences of *using system feedback* to develop the subsequent hypothesis; 1 point: some evidences of *using system feedback* to develop the subsequent hypothesis; 0 point otherwise
Quality of justification of the hypothesis	8 points total: There are two questions per question prompt. 2 points for a clear and correct answer to each question, and 2 points for strong logical justification responding to each question. Deduct 1 point per question if the response is not elaborated clearly.

In addition, *complex learning* was measured by rating participants' hypothesis, hypothesis justification, and explanation of the results in the inquiry cycles to see if a participant is developing a comprehensive understanding of the lake ecology system and the dynamic interrelationships among its variables. In other words, whether students are able to (1) identify various variables affecting the lake ecosystem (for example, fungi, bacteria, green algae, diatoms, sun energy, CO_2, O_2, nutrients, etc.), and (2) identify the interrelationships among these variables (for example, diatoms produce the oxygen that fuels bacterial respiratory processes, while bacteria generates the $C0_2$ and nutrients that diatoms require for driving their photosynthetic processes. Both diatoms and bacteria die, of natural causes, feeding the stock of detritus. That stock, in turn, nourishes bacteria that then decompose detritus to create the nutrients that diatoms require for nourishment.) The scoring rubric of the complex learning measured is shown in Table 2.

Two raters coded all protocols based on the analytical rubric system developed by the research team. The interrater reliability was 95% for cognitive regulation measure and 90% for complex learning measure. Any discrepancies of assigned scores were discussed among the raters and the adjudicated score was used. Consequently, a high consensus was reached. Repeated measures ANOVA analysis was conducted to examine change on *cognitive regulation* and *complex learning* measures both after challenge 1, after challenge 2, and after challenge 3 in the *Food Chain* simulation.

Results

Table 3 summarizes the descriptive statistics for the two dependent variables (cognitive regulation and complex learning) for both control (QP) and experimental (MP) groups along the three challenges: (T1) simpler complex problem where no scaffolding was provided from the system; (T2) more complex problem scaffolded with either QP or MP; and (T3) very complex, environmental policy analysis problem scaffolded with either QP or MP. Below is the statistical analysis report in response to each of the hypotheses tested.

Table 2: Overview of the scoring rubric for *complex learning* measure

Coding Category	Number of points given
Correct variables	2 points: all correct variables are identified; 1 point: some correct variables are identified; 0 otherwise.
Energy cycle	1 point: evidences of understanding that plants harness energy from the sun; 0 point otherwise
CO_2/O_2 cycle	4 points: evidences of understanding that some species are providing CO_2 and consuming O_2 in the ecosystem and other species are providing O_2 and consuming CO_2 in the ecosystem; deduct one point each if the students could not identify CO_2 , O_2, consumption or production cycle.
Nutrient cycle	3 points: evidences of understanding that species are providing for other species for nutritional needs; deduct one point each if (1) the student identify do not have the complete food cycle, (2) cannot identify decomposer role in the system, and (3) do not give a clear explanation.

Table 3. Descriptive statistics for cognitive regulation and complex learning measures

Measures	Control (QP) Group						Experimental (MP) Group					
	Mean			Std. Dev.			Mean			Std. Dev.		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Cognitive Regulation	2.01	4.21	5.72	1.03	1.13	1.95	1.97	4.15	6.20	0.96	1.70	2.16
Complex Learning	1.84	3.45	4.33	0.89	0.49	1.16	1.64	3.75	6.92	1.04	0.89	1.30

Effects on Cognitive Regulation

The first research question asked whether scaffolding with question prompts and system dynamics model progressions affect student cognitive regulation in the process of developing solutions to complex problem scenarios.

As evident in the descriptive statistics shown in Table 2, participants in the MP condition had lower mean scores than the participants in the QP condition in *cognitive regulation* after the first challenge in the *Food Chain*, during which no cognitive regulation scaffolding was provided by the system. However, the repeated measures ANOVA analyses did not indicate significant differences between the two groups in these two dependent variables $F\ (2,\ 209) = 0.47$, $p > .05$, $\eta^2 = .025$. The results indicated that the participants in both conditions were comparably on equal basis after they completed the first challenge.

However, the repeated measures ANOVA analyses revealed a significant main effect in participants' cognitive regulation of inquiry learning in both QP and MP conditions between the first challenge, where no scaffolding were provided by the system, and the second challenge, where participants received either scaffold $F\ (2,\ 209) = 0.47$, $p > .05$, $\eta^2 = .025$, which supported the hypothesis that students, when received either cognitive regulation scaffold, would perform significantly better than when cognitive regulation was not scaffolded during inquiry learning. Nevertheless, after completing the second challenge in the *Food Chain* simulation-based inquiry-learning environment, the repeated measures ANOVA analyses did not indicate significant differences between the two groups with respect to their cognitive regulation skills.

After the third challenge, which included a very complex environmental policy making problem, the repeated measures ANOVA analyses revealed a significant main effect in favor of the MP group, $F\ (2,\ 209) = 0.47$, $p > .05$, $\eta^2 = .025$, which supported the hypothesis that, in highly complex learning tasks, providing students with annotated system dynamic model progression was more effective than question prompting as a cognitive regulation scaffold in simulation-based inquiry learning.

Effects on Complex Learning

The second research question asked whether scaffolding with question prompts and system dynamics model progressions affect students' learning about complex systems, hence, complex problem-solving skill acquisition.

As seen in Table 2, participants in the MP condition had lower mean scores than the participants in the QP condition in *complex learning* after the first challenge in the *Food Chain* simulation-based inquiry-learning environment, during which no cognitive regulation scaffolding was provided by the system. However, the repeated measures ANOVA analyses did not indicate significant differences between the two groups in these two dependent variables $F\ (2,\ 209) = 0.47$, $p > .05$, $\eta^2 = .025$. The results indicated that the participants in both conditions were comparably on equal basis when they completed the first challenge.

However, the repeated measures ANOVA analyses revealed a significant main effect in participants' cognitive regulation of inquiry learning in both QP and MP conditions between the first challenge, where no scaffolding were provided by the system, and the second challenge, where participants received either scaffold $F\ (2,\ 209) = 42.66$, $p < .01$, $\eta^2 = .53$, which supported the hypothesis that students, when received either cognitive regulation scaffold, would learn about complex systems better than when cognitive regulation was not scaffolded during inquiry learning. Nevertheless, after completing the second challenge in the *Food Chain* simulation-based inquiry-learning environment, the repeated measures ANOVA analyses did not indicate significant differences between the two groups with respect to complex learning.

For the third challenge, which included a very complex environmental policy making problem, the repeated measures ANOVA analyses revealed a significant main effect in favor of the MP group, $F\ (2,\ 209) = 49.86$, $p < .01$, $\eta^2 = .57$, which supported the hypothesis that, in highly complex learning tasks, providing students with annotated system dynamic model progression was more effective than question prompting to support students' learning of complex ecology systems during simulation-based inquiry learning.

Discussion

The purpose of this study was to investigate the effects of two promising cognitive-regulation scaffolding strategies, *question prompts* and *model progression*, on ninth-grade biology students' (1) cognitive regulation of inquiry learning; and (2) learning of a complex system (lake ecosystem) in a simulation-based inquiry-learning environment. This study also addressed the effect of task complexity on the effectiveness of students' cognitive regulation and their successful learning in complex systems.

The results of this study pointed out to a number of important issues. First, the results showed that both scaffolding strategies were effective in providing the cognitive regulation support for students using a simulation-based inquiry-learning system. However, as the complexity of the problem increased, model progression was significantly more effective than question-prompts. This is consistent with earlier studies, which suggested the ineffectiveness of question prompting as a self-regulation scaffold in situations where students have insufficient prior knowledge, which plays an important role in elaborated learning (Ge & Land, 2003; Greene & Land, 2000; King, 1992).

This finding also explains some of the mixed results in earlier studies regarding the effect of model progression on self-regulation. For instance, Quinn and Alessi (1994) performed a study, in which students has access to a simulation of a spread of a disease within a simulation. Students had to manipulate two to four input variables to minimize the value of one of the output variables. Their data revealed that model progression had no overall positive effect on performance. It should be noted, however, that the domain that was used by Quinn and Alessi (1994) was quite simple: the variables in the model did not interact. In another study with simulation of a more complex system (multimeter) Alessi (1995) found that model progression was beneficial for initial learning and for transfer. Similar positive results were observed in Rieber and Parmley's (1995) study in the area of Newtonian motion.

Secondly, the results of this study confirmed the findings from the earlier studies, which suggested using question-prompts as a self-regulation support early in the simulation. For instance, Showalter (1970) recommended using question-prompts early in the simulation to focus learner attention to specific aspects of the simulation. Similar studies by Zietsman and Hewson (1986), Tabak, Smith, Sandoval, and Reiser (1996), White (1984; 1993) also pointed out to the effectiveness of such strategy in different domains for providing self-regulation (especially for planning) support during simulation-based inquiry learning.

Finally, this study provided empirical evidence for the link between cognitive-regulation skills and learning in complex systems (i.e., complex problem-solving), which was suggested in earlier studies (see Butler & Winne, 1995; Davis, 2000; Lin & Lehman, 1999; Schraw, 1998). In this regard, there was no significant difference between the impact of question-prompts or model progression when the problem was a simpler complex problem. However, as the complexity of the problem increased, cognitive scaffolding by model progression had significantly higher impact on learning than cognitive scaffolding by question-prompts.

In future studies, it would be beneficial to investigate the effectiveness of both scaffolding strategies on far-transfer complex problem-solving tasks. These studies should also factor in individual student differences and investigate whether there are differences among low-achieving and high-achieving students. Students who participated in our study had not received any prior instruction on lake ecosystems; the domain-specific knowledge required for inquiry learning was constantly accessible, on demand, in the *Food Chain* simulation environment. Directions included in the system encouraged students to read the domain-specific information prior to generating hypothesis. Therefore, in this study, an attempt was made to bring individual differences to a minimum possible level in order to rule out confounding factors that might have affected the results of this investigation.

Overall, this study provided empirical evidence to the critical importance of embedding appropriate feedback strategies in technology-based learning environments (see Cohen, 1985). This corresponds with the current discussion about the failure of the popular movements of constructivist learning environments adopting discovery, problem-based, experiential, and inquiry-based teaching approaches and provide support to the arguments by Kirschner et al. (2006) and Mayer (2004). We hope to see more studies investigating the effectiveness of technology-mediated scaffolding strategies so that an appropriate design theory for instructional simulations may arise. Current attempts, though interesting, are necessarily fragmentary and incomplete (Thurman, 1993; de Jong & van Joolingen, 1998). Coupled with such a theory, inquiry learning with simulations can fulfill its promise in learning and instruction.

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