Interactive Metacognition:

Monitoring and Regulating a Teachable Agent

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Metacognition involves monitoring and regulating thought processes to make sure they are working as effectively as possible (Brown, 1987; Flavell, 1976; Winne, 2001). Good teachers are highly metacognitive (Lin, Schwartz, & Hatano, 2005). They reflect on their expertise and instruction, and they refine their pedagogy accordingly. Good teachers are also metacognitive in a less conventional sense of the term. They monitor student understanding and they regulate the processes students use to learn and solve problems (Shulman, 1987). Thus, good teachers apply metacognition to other people's thoughts. The proposal of this chapter is that asking children to teach and apply metacognition to others can help them learn both content knowledge and metacognitive skills. A strong version of this proposal, consistent with Vygostky (1987), would be that metacognition develops first on the external plane by monitoring others, and then turns inward to self-monitoring. The chapter does not test this claim. Instead, it shows that having students teach a specially designed computer agent leads to metacognitive behaviors that increase content learning and hint at improving metacognition more generally.

To differentiate self-directed metacognition and other-directed metacognition, we term the latter "interactive metacognition." Learning-by-teaching is an instructional method that is high on interactive metacognition – tutors anticipate, monitor, regulate, and more generally, interact with their tutees' cognition. Research on learning-by-teaching has found that teaching another person is an effective way to learn. For instance, when people prepare to teach pupils to take a test, they learn more compared to when they prepare to take the test themselves (Annis, 1983; Bargh & Schul, 1980; Biswas et al., 2001; cf. Renkl, 1995). Moreover, during the act of teaching, tutors learn by clarifying the confusions of their tutees (Craig, Sullins, Witherspoon, & Gholson, 2006; Palinscar & Brown, 1984; Uretsi, 2000) and by engaging in reflective knowledge building (Roscoe & Chi, 2008). Interestingly, when tutors slip into “lecturing mode” and no longer engage in interactive metacognition, they learn less (Chi, Roy and Hausmann, 2008; Fuchs, Fuchs, Bentz, Phillips, & Hamlett, 1994; Graesser, Person, & Magliano, 1995; Roscoe & Chi, 2007).

The interactive quality of other-directed metacognition can help resolve two psychological challenges: balancing the dual-task demands of metacognition; and, rallying the motivation to engage in metacognition. Metacognition puts a dual-task load on working memory. During metacognition, people need (1) to think their problem-solving thoughts, and they simultaneously need (2) to monitor and regulate their thinking about those thoughts. When learning or problem solving becomes difficult, there can be less free capacity for metacognition. For example, when first learning to drive a car with a manual transmission, people may be less likely to monitor their knowledge of the cars behind them. Teaching can help alleviate the dual-task demand of metacognition. The tutee has the responsibility of problem solving, which frees up resources for the tutor’s metacognition. Gelman and Meck (1983), for example, found that young children could monitor errors in adult counting better than their own counting, when the counting task reached the edge of the children’s abilities (cf. Markman, 1977). In this case, interactive metacognition was a form of distributed cognition (King, 1998; Kirsch, 1996), where the adult took on the burden of problem solving and the child took on the burden of monitoring that problem solving.

The distribution of tasks in interactive metacognition can help students improve their own metacognition, because they can focus on monitoring and regulating cognition *per se*. For example, in a series of studies by Okita (2008), elementary school children learned tricks for mentally solving complex arithmetic problems. In half of the cases, students practiced problem solving on their own. In the other half of the cases, students took turns. On one turn, they would try to solve a problem, and on the next turn, they would monitor a computer agent solving a problem. The children had to stop the agent if they thought there was a mistake. Students who monitored the agent demonstrated a U-shaped curve in their own problem solving. When first monitoring the agent, students subsequently became slower and less accurate in their own problem solving. Over time, however, the children sped up and became more accurate compared to students who never monitored the agent. Presumably, by monitoring the agent, the students were learning to monitor themselves, which caused a temporary drop in efficiency, but a better payoff in the long run, because they improved their own cognition.

The second challenge of metacognition is motivational. Because metacognition takes extra work, people will tend to "get by" if they can, rather than take the extra cognitive effort needed to go beyond "good enough" (Martin & Schwartz, accepted). Students often skim readings, because they think it is not worth checking their understanding. Teachers, however, are responsible for their students' performance, not to mention their own display of competence. This increase in responsibility can motivate teachers to engage in interactive metacognition, which may be one reason that tutors learn more when preparing to teach than simply studying for themselves (e.g., Annis, 1983).

This chapter reviews research on Teachable Agents to demonstrate that it is possible to use computer learning environments to produce the cognitive and motivational benefits of interactive metacognition. Teachable Agents (TA) are learning-by-teaching environments where students explicitly teach an intelligent computer agent. The chapter begins with an introduction of the TA, “Betty’s Brain,” followed by a description of how Betty elicits interactive metacognitive behaviors. The chapter then shows that teaching Betty improves children’s content learning and their abilities to use the same sort of reasoning as Betty. Finally, the chapter examines students’ learning choices to determine whether they begin to internalize interactive metacognition.

A Technology for Applying Interactive Metacognition

This section explains how the Teachable Agent software naturally engages metacognition during learning. Betty’s Brain, the TA shown in Figure 1 and the focus of this chapter, was designed for knowledge domains where qualitative causal chains are a useful structural abstraction (e.g., the life sciences). Students teach Betty by creating a concept map of nodes connected by qualitative causal links; for example, ‘burning fossil fuels’ increases ‘carbon dioxide’. Betty can answer questions based on how she was taught. For instance, Betty includes a simple query feature. Using basic artificial intelligence reasoning techniques (see Biswas, Leelawong, Schwartz, Vye, & TAG-V, 2005), Betty animates her reasoning process as she answers questions. In Figure 1, Betty uses the map she was taught to answer the query, “What happens to ‘heat radiation’ if ‘garbage’ increases?” Students can trace their agent’s reasoning, and then remediate their agents’ knowledge (and their own) if necessary. As described below, there are many feedback features that help students monitor their agent’s understanding. A version of the

Betty's Brain environment and classroom management tools can be found at <aaalab.stanford.edu/svBetty.html>. Betty is not meant to be the only means of instruction, but rather, she provides a way to help students organize and reason about the content they have learned through other classroom lessons.

[Figure 1 about here – Betty's Brain]

In reality, when students work with Betty, they are programming in a high-level, graphical language. However, Betty's ability to draw inferences gives the appearance of sentient behavior. Betty also comes with narratives and graphical elements to help support the mindset of teaching; for example, students can customize their agent's appearance and give it a name. ("Betty's Brain" is the name of the software, not a student's specific agent.) Betty can also take quizzes, play games, and even comment on her own knowledge. Ideally, the TA can enlist students' social imagination so they will engage in the processes of monitoring and regulating their agent's knowledge.

A key element of Betty is that she externalizes thought processes. Betty literally makes her thinking visible. Thus, students are applying metacognition to the agent's thinking and that thinking is in an easily accessible format.

Monitoring One's Own Thoughts in an Agent

For students to practice metacognition on their agent, they need to view Betty as exhibiting cognitive processes. This section shows that students do treat their agent as sentient, which leads them to take responsibility for monitoring and regulating their agents' knowledge. It then shows that Betty's knowledge is a fair representation of the students' own knowledge, which shortens the distance between monitoring the agent and monitoring themselves.

The Agent Elicits Interactive Metacognitive Behaviors

When programming and debugging their agents, students are also monitoring and regulating their agents' knowledge and reasoning. A study with 5th-graders demonstrated that students treat their agents as having and using knowledge. By this age, children know the computer is not really alive, but they suspend disbelief enough to treat the computer as possessing knowledge and feelings (e.g., Reeves and Nass, 1996; Turkle, 2005). Students monitor their agents' failures and share responsibility, which leads them to revise their own understanding so they can teach better.

The study used the Triple-A-Challenge Gameshow, which is an environment where multiple TAs, each taught by a different student, can interact and compete with one another (Figure 2). Students can log on from home to teach their agents, chat with other students, and eventually have their agents play in a game. During game play, (1) the game host poses questions to the agents; (2) the students choose a wager that their agent will answer correctly; (3) the agents answer based on what they have been taught; (4) the host reveals the correct answer; and finally, (5) wager points are awarded. In addition to boosting engagement, the wagering feature was intended to lead students to think through how their agent would answer the question, thereby monitoring their agent's understanding. The Gameshow was developed to make homework more interactive, social, and fun. In this study, however, the focus was on student attitudes towards Betty during game play, and students were videotaped as they worked alone.

[Figure 2 about here – Gameshow podium]

The study included two conditions. In both, students received a text passage on the mechanisms that sustain a fever, and they taught their TA about these concepts. The treatment difference occurred when playing the Gameshow. In the TA condition, the agents answered six questions, and the graphical character in the Gameshow represented the agent. In the Student condition, the students answered the questions, and the character represented the student. To capture students' thoughts and feelings towards the agent, students in both groups thought aloud.

In the TA condition, students treated their agents as having cognitive states. Students' attributions of cognitive states were coded as being directed to themselves, their agents, or both. Examples of self-attributions include, "It's kind of confusing to me," "I have a really good memory," and "No, actually, I don't know." Examples of agent-attributions include, "He doesn't know it," and "He knows if shivering increases…." Sometimes, a single statement could include both self and agent attributions; for example, "I'm pretty sure he knows this one," and, "I guess I'm smarter than him."

During game play, students in both treatments made about two cognitive state attributions per question. For the TA condition, over two-thirds of these attributions were towards the agent or a combination of agent and student. Thus, students treated the agent as a cognitive entity, and in fact, they sometimes confused who was doing the thinking, as in the case of one boy, who stated, "'cause I don't… 'cause he doesn't know it."

The TA students also took an "intentional stance" (Dennett, 1989) towards their agents, by apportioning responsibility to the agent for success and failure. They could have behaved as though all successes and failures were theirs, because the agent is simply a program that generates answers from a map the student had created, but they did not. Table 1 indicates the number of attribution-of-credit statements made in response to successful and unsuccessful answers. Examples of success attributions include, “I’m glad I got it right” (self), “He got it right!” (agent), or “We got it!” (both). Examples of failure attributions include, “I didn’t teach him right” (self), “He said *large* increase when it was only increase” (agent), or “Guess we were wrong” (both).

[Table 1 about here – attributions of sentience]

As the table shows, students in the TA condition liberally attributed responsibility to the agent. Importantly, the TA condition exhibited more attention to failure, which is a key component of monitoring (e.g., Zimmerman & Kitsantas, 2002). They made nearly three times as many remarks in a failure situation relative to the Student condition. The attributions were spread across themselves and their agents. In addition to acknowledging failure, they often made remarks about flaws in their teaching such as, “Whoa. I really need to teach him more.” Thus, at least by the verbal record, the TA condition led the students to monitor and acknowledge errors more closely than the Student condition.

The study also demonstrated that the students were sufficiently motivated by teaching to engage in the extra work that metacognition often entails. After completing the round of game play, students were told the next round would be more difficult. They were given the opportunity to revise their maps and re-read the passage in preparation. While all the children in the TA condition chose to go back and prepare for the next round, only two-thirds of the Student condition prepared. Of those who did prepare, the TA students spent significantly more time at it. The protocol data from the game play help indicate one possible reason. The Student condition exhibited nearly zero negative responses to failure (e.g., “Ouch!). Given an unsuccessful answer, the Student condition averaged 0.02 negative affective responses. In contrast, the TA condition averaged 0.62 expressions of negative affect. Much of this negative affect was regarding their agent’s feelings. For example, one student said “Poor Diokiki… I’m sorry Diokiki” when his agent, Diokiki, answered a question incorrectly. The TA students felt responsibility for their agents’ failures, which may have caused them to spend more time preparing for the next round of game play.

Overall, these data indicate that the children treated their agents as if they were sentient, which had subsequent effects on student learning behaviors. In reality, the children were “playing pretend.” They knew their agent was not a sentient being. Regardless, their play involved the important features of metacognition – thinking about mental states and processes, noticing and taking responsibility for mistakes, and experiencing sufficient affect that it is worth the effort to do something about the mistakes when given a chance to revise. Working with another, in this case an agent one has taught, can lead to more metacognitive behaviors than completing a task oneself.

The Agent’s Knowledge Reflects the Student’s Knowledge

Schoenfeld (1987), discussing the importance of monitoring, states that “… the key to effective self-regulation is being able to accurately self-assess what is known and not known.” In Betty, students are assessing what their agent does and does not know. The agent’s knowledge is a reflection of their own knowledge, so that working with the agent indirectly entails working on an externalized version of their own knowledge. This was demonstrated by correlating the test scores of the students and their agents.

Betty can be automatically tested on the complete population of questions in a concept map. By using a hidden expert map that generates the correct answers, the program can successively test Betty on all possible questions of the form, “If node <X>

increases, what happens to node <Y>?" The results produce an *APQ Index* (all possible questions) that summarizes the overall test performance of the TA.

A study with 30 sixth-grade students compared the agents' APQ indices with how well students did on their own paper-and-pencil tests. Students completed three cumulative units by teaching their agents about global warming and climate change. At the end of each unit, the agents were tested to derive an APQ Index, and students took a short answer, paper-and-pencil test. In the paper-and-pencil test, half of the items comprised TA-like questions, in the sense that they depended on causal chaining and nodes in Betty's map. The other half comprised Non-TA questions in the sense that they depended on content that was not captured in Betty's nodes. The Non-TA questions helped to determine whether Betty correlated with student knowledge more broadly, and not just questions that Betty could answer.

[Table 2 about here – APQ x Student test scores]

Table 2 indicates that the TA scores were positively correlated with students' test scores. These correlations compare favorably with the correlations between students' scores on the TA-like questions and the Non-TA questions for each unit test (Test 1: r = .47; Test 2: r = .46; and Test 3: r = .14. Thus, the APQ Index correlated better with student performance on the TA-like and Non-TA questions than these two types of paper-and-pencil items correlated with each other. (The low correlations for Test 3 are due to a badly worded TA-like question.) Conceivably, with further development and evaluation, it will be possible to test agents instead of students, thereby saving valuable instructional time.

The correlation of student and agent performance indicates that when students monitor their agent's knowledge, for example, by asking it a question, they are likely to be monitoring a fair externalization of their own knowledge. This helps to dissolve the gap between self and other, so that the task of working with the agent is a proxy for the task of reflecting upon their own knowledge.

Adopting the Cognition of the Agent

Given that students treat the TA as exhibiting mental states and the TA reflects the student's knowledge, the next question is whether these have any effect on student learning. Ideally, by monitoring another's cognition, one can pick up the other person's style of reasoning. Siegler (1995), for example, found that young children learned number conservation more effectively when prompted to explain the experimenter's reasoning rather than their own. Betty reasons by making inferences along causal chains. When students teach Betty, they learn to simulate her causal reasoning for themselves.

Learning to simulate Betty's cognition about a situation is different from learning to simulate the situation itself. When people reason about a situation itself, they often create a mental model that helps them imagine the behavior of the situation and make predictions (Gentner & Gentner & Stevens, 1983; Glenberg, et al., 2004; Zwaan & Radvansky, 1998). For example, when reasoning about how gears work, people can create and simulate an internal image of the gears to solve problems (Schwartz & Black, 1996). To run their mental model, people imagine the forces and movements of the gears, and they observe the resulting behaviors in their mind's eye. With Betty, students create a mental model of the agent's reasoning. So, rather than simulating forces and spatial displacements, the students learn to simulate chains of declarative reasoning. This way, Betty's cognition becomes internalized as a way of reasoning for the student.

Relevant data come from the preceding study where two classes of sixth graders learned about global warming. Over two weeks, students learned the mechanisms of the greenhouse effect, the causes of greenhouse gasses, and finally, the effects of global warming. Both classes completed hands-on activities, saw film clips, received lectures, and completed relevant readings. At regular points, students were asked to create concept maps to organize their learning, and they all learned how to model causal relations using a concept map. The difference was that one class was assigned to the Betty condition; these students used the Betty software to make their concept maps. Figure 3 shows a finished "expert" version of a map created on the Betty system. The other class was assigned to the Self condition; these students used *Inspiration*®, a popular, commercial concept-mapping program.

[Figure 3 about here – Global Warming Map]

Students in both conditions received multiple opportunities for feedback with an important difference. In the Betty condition, agents answered the questions, and the feedback was directed towards the agents. In the Self condition, the students answered the questions, and the feedback was directed towards them. This difference occurred across several feedback technologies. For example, the agents took quizzes or the students took quizzes. For homework, the agents answered questions in the Gameshow or the students answered the questions in the Gameshow. Thus, the main difference between conditions was that in the Betty condition, the learning interactions revolved around the task of teaching and monitoring the agent, whereas in the Self condition, the learning interactions revolved around the task of creating a concept map and answering questions and monitoring oneself.

[Figure 4 about here – accuracy by inference chain length]

The students in the Betty condition adopted Betty's reasoning style. After each unit – mechanisms, causes, effects – all the students completed short-answer, paper-pencil tests. The tests included questions that required short, medium, or long chains of causal inference. An example of a short-chain question involved answering why warmer oceans increase sea level. An example of a long-chain question involved detailing a causal bridge that spanned from an increase in factories to the effects on polar bears. Figure 4 shows that over time the Betty students separated from the Self students in their abilities to complete longer chains of inference. After the first unit, the two groups overlapped, with the Betty students showing a very modest advantage for the longer inferences. After the second unit, the TA students showed a strong advantage for the medium-length inferences. By the final unit, the TA students showed an advantage for short, medium, and long inferences.

This study used intact classes, so the results are promissory rather than conclusive. Nevertheless, the steady improvement in length of causal inference is exactly what one would expect the Betty software to yield, because this is what the agent's reasoning models and enforces. The interactive metacognition of teaching and monitoring Betty's reasoning and accuracy helped students internalize her style of thinking, which in this case, is a positive outcome because her reasoning involved causal chaining.

Regulating Cognition for the Agent

In addition to monitoring cognition, metacognition involves taking steps to guide cognition, or as it is often termed, “regulating” cognition (Azevedo & Hadwin, 20055; Brown, 1987; Butler & Winne, 1995; Pintrich, 2002; Schraw, Crippen, & Hartley, 2006). Regulating another can help students learn to regulate for themselves.

Thus far, Betty’s features supported monitoring, but there were few features to help students decide what to do if they detected a problem. For example, one student’s agent was performing poorly in the Gameshow and the student did not know how to fix it. The Gameshow was not designed to address this situation. Fortunately, another student used the Gamehow’s chat feature to provide support, “Dude, the answer is right there in the reading assignment!”

To help students learn to self-regulate their thinking, Betty comes in a self-regulated learning (SRL) version. For example, when students add incorrect concepts or links, Betty can spontaneously reason and remark that the answer she is deriving does not seem to make sense. This prompts students to reflect on what they have just taught Betty and to appreciate the value of checking understanding. SRL Betty also includes Mr. Davis, a mentor agent shown in Figure 5. Mr. Davis complements the teaching narrative, because he grades Betty’s quizzes and gives her feedback on her performance. This feedback is in the form of motivational support (e.g., “Betty, your quiz scores are improving”), as well as strategies to help the students improve Betty’s knowledge (e.g., “Betty, ask your teacher to look up the resources on quiz questions that you have got wrong …”).

[Figure 5 – Mr. Davis]

SRL Betty implements regulation goals specified in Zimmerman's (1989) list of self regulation strategies. The SRL system monitors for specific patterns of interaction, and when found, Betty or Mr. Davis provide relevant suggestions (also see Jeong, et al., 2008). Table 3 provides a sample of triggering patterns and responses used by the SRL system; there are many more than those shown in Table 3.

[Table 3 about here – SRL Patterns and Responses]

In sum, SRL Betty is an adaptive tutoring system, except that students are the tutors, and the system adapts to target metacognitive needs specifically. The metacognitive support is integrated into the teaching narrative through computer characters that take the initiative to express opinions, make requests, and provide relevant prompts to encourage further interactive metacognition. In the following, the first sub-section shows that SRL support helps students learn science content. The second sub-section introduces a new machine learning methodology for analyzing student choices. The methodology is used to identify high-level interaction patterns that indicate metacognitive strategies. It is then used to evaluate whether students developed metacognitive strategies that they continued to use on their own, even when the SRL features were turned off.

Self –Regulation Support Improves Student Learning

The self-regulation support in SRL Betty helps students learn science content better. Fifty-one 5^{th}-grade students learned about interdependence in a river ecosystem with a special focus on the relations between fish, macroinvertebrates, plants, and algae. The students worked over seven class periods starting with the food chain, then photosynthesis and respiration and finally the waste cycle. To help the students learn, there were quizzes and reading resources built into the system. (In the Gameshow studies described earlier in the chapter, the students received the nodes, and their task was to determine the links. In this study, the students had to decide which nodes to include in their maps based on the reading, so they could develop strategies for identifying key concepts.)

The study had three conditions: Regulated Learning by Teaching (RT); Learning by Teaching (LT); and Intelligent Coaching (IC). The RT condition used SRL Betty, per Table 3. Students could also submit Betty to take a quiz, and Mr. Davis provided metacognitive tips about resources and steps the students could use to teach Betty better. Mr. Davis did not dictate specific changes to Betty's knowledge, for example, to add a particular concept or change a link. Instead, he suggested strategies for improving Betty's knowledge (e.g., "Check if Betty understands after you have taught her something new").

In the LT condition, students worked with Betty and the mentor agent, but without the SRL support. Betty did not provide prompts for regulating how she was taught, and Mr. Davis provided direct instructions for how to fix the concept map after a quiz. For example, Mr. Davis might tell students "to consider how macroinvertebrates might affect algae and add an appropriate link."

The final Intelligent Coach (IC) condition was identical to the LT condition, except that students used the software to make concept maps of their own knowledge. There was no teaching cover story. Instead of asking Betty to answer a question, students could ask Mr. Davis to answer a question using the concept map or to explain how the map gave a certain answer. Thus, students got the same information and animations as in the LT condition, except they thought it was their map that Mr. Davis was analyzing instead of Betty's thinking.

In addition to the initial seven days of learning, the study included a second learning phase that measured transfer. Six weeks after completing the river ecosystem unit, students left their original conditions to spend five class periods learning about the land-based nitrogen cycle. All the students worked with a basic Betty version. There were on-line reading resources; Betty could answer questions; and, students could check how well Betty did on quizzes. However, there was no extra support, such as how to improve Betty's map or their teaching. The logic of this phase was that if students had developed good metacognitive strategies, they would be more prepared to learn the new content on their own (Bransford & Schwartz, 1999).

The students' final concepts maps from the main and transfer phases were scored for the inclusion of correct nodes and links based on the reading materials. Table 4 holds the average scores. Overall, both conditions that involved teaching did better than the Intelligent Coach condition, with no interactions by time. This means that the Learning-by-Teaching condition did better than the Intelligent Coach condition, even though the only treatment difference between these two conditions was whether students thought they were teaching and monitoring Betty (LT), instead of being monitored by Mr. Davis (IC). This result reaffirms the findings from the global warming study using a tighter experimental design. If students believe they are teaching an agent, it leads to superior learning even when they are using the same concept mapping tool and receiving equivalent feedback.

In a separate study not reported here, an Intelligent Coaching condition included self-regulated learning support, similar to the Regulated Teaching condition. (Mr. Davis gave prompts for how to improve the concept map by consulting resources, checking the map by asking queries, etc.). In that study, the IC+Regulated support condition did no better than an IC condition, whereas the RT condition did. So, despite similar levels of metacognitive prompting, the prompting was more effective when directed towards monitoring and regulating one's agent. This result also supports the basic proposition that teaching effectively engages metacognitive behaviors, even compared to being told to use those metacognitive behaviors for one's self.

[Table 4 about here – Concept Map Scores]

Post-hoc analyses of the main learning phase indicates that the extra metacognitive support of the RT treatment led to better initial learning than the LT condition in which students did not receive any guidance on regulation. However, once students lost the extra support in the transfer phase, they performed about the same as the LT students. By these data, self-regulation support helped students learn when it was available, but it is not clear that the extra support yielded lasting metacognitive skills compared to only teaching Betty. As described next, however, there were some modest differences in how the RT students went about learning in the transfer phase, even though these did not translate into significant learning differences.

Adopting Metacognitive Learning Choices from an Agent

Metacognition, besides helping people think more clearly, can also help people make choices about how to use learning resources in their environment. For example, to study for the California Bar exam, many students order the BAR/BRI materials (www.barbri.com). These materials comprise nearly a cubic meter of readings, reviews, outlines, practice tests, videotapes, as well as live local lectures, workshops and on-line tutorials. Across the materials, the content is highly redundant. Rather than plowing through all the materials, these well-educated adults often choose the presentation format and activities that they feel suit their learning needs and preferences for a particular topic. Their learning is driven by their choices of what, when, and how to learn. Outside of classrooms that exert strict control, this is often the case. People make choices that determine their learning. For younger students, metacognitive instruction should help children learn to make effective learning choices.

[Table 5 about here – Possible student choices]

This section introduces a new data mining methodology for examining learning choices. The goal is to be able to identify choice patterns that reflect effective metacognition. Ideally, once these patterns have been identified, adaptive technologies can monitor for these patterns and take appropriate actions. This is a useful endeavor, because current adaptive computer systems depend on strict corridors of instruction in which students can make few choices (except in the unrelated sense of choosing an answer to a problem). If students do not have chances to make choices during learning, it is hard to see how they can develop the metacognition to make effective learning choices. If the current methodology (or others) is successful, it will be possible to use more choice-filled learning environments, like virtual worlds, without sacrificing the benefits of adaptive technologies for helping students to improve.

To explore the data mining methodology, it was applied to the log files from the preceding study. The question was whether the methodology could help reveal whether the RT students exhibited unique patterns of learning choices during the initial learning phase when the metacognitive support was in play, and whether these patterns carried over to the transfer phase when the support was removed. That is, did the students in the RT condition internalize the metacognitive support so they exhibited effective metacognitive patterns once the support was removed?

In the study, students could make a number of choices about which activities to pursue. Table 5 summarizes the possibilities. For example, one student read the resources, and then made a number of edits to the map. Afterwards, the student submitted the map to a quiz, made some more edits, and then asked a pair of questions of the map. In raw form, the logfile sequence is somewhat overwhelming: R → M → M → M → A → M → M → M → M → M → M → M → M → M → Q → M → M → A → A.

To make sense of these complex choice sequences, a new data mining methodology analyzed the log files (Li and Biswas, 2002; Jeong & Biswas, 2008). The methodology automated the derivation of a Hidden Markov Model (HMM). An HMM model represents the probabilities of transitioning between different “aggregated” choice states (Rabiner, 1989). An aggregated choice state represents common choice patterns that comprise sequences of individual choices to transition from one activity to another. HMM is useful for identifying high-level choice patterns, much in the way that factor analysis is useful for identifying clusters of survey items that reflect a common underlying psychological property.

The HMM analysis generated three choice patterns that could be interpreted as increasing in metacognitive sophistication: Basic Map Building; Map Probing; and, Map Tracing. The Basic Map Building pattern involves editing the map, submitting the map for a quiz, and occasionally referring to the reading resources. It reflects a basic and important metacognitive strategy. Students work on their maps, check the map with a quiz to see if there are errors, and occasionally look back at the readings. Students may order these choices in different ways, but HMM analysis captured that students frequently transitioned among these choices.

In the Map Probing pattern, students edit their maps, and then they ask a question of their map to check for specific relations between two concepts (e.g., if fish increase, what happens to algae?). This pattern exhibits a more proactive, conceptually driven strategy. Students are targeting specific relations rather than relying on the quiz to identify errors, and students need to formulate their own questions to check their maps.

Finally, the Map Tracing pattern captures when students ask Betty or Mr. Davis (depending on the system) to explain the steps that led to an answer. When Betty or Mr. Davis initially answers a question during Map Probing, the agents only state the answer and show the paths they followed. To see whether a specific link within the path produced an increase or decrease, students have to request an explanation. (Map Tracing can only occur after Map Probing.) These decomposing explanations are particularly useful when maps become complex, and there are multiple paths between two concepts. Map Tracing is a sophisticated metacognitive strategy, because it involves decomposing a chain of reasoning step-by-step, even after the answer has been generated in Map Probing.

[Figure 6 about here. HMM transition probabilities]

Figure 6 shows the complete set of transitional probabilities from one state to another broken out by condition and phase of the study. The figure is complex, so the following discussion will narrow the focus to Map Tracing.

Multiplying the transition probabilities yields a rough estimate of the proportion of time students spent in a specific activity state. This is important, because just looking at a single transition can be misleading. For example, in the main phase of the study, the IC and RT conditions transitioned from Map Probing into Map Tracing at the same rate. Nevertheless, the IC condition spent much less time Map Tracing. The IC students rarely transitioned from Map Building into Map Probing, and Map Probing is a necessary precursor to Map Tracing.

In the first phase of the study, students in all three conditions spent a significant proportion of their time in Basic Map Building. However, the RT (Regulated Teaching) students more often transitioned into Map Probing and Map Tracing. Their version of the software included two features to make this happen. First, Betty would not take a quiz if students had not checked her reasoning by asking her a question. This forced students to enter the Map Probing activity. Second, Betty and Mr. Davis suggested that the students ask Betty to explain her reasoning, so the students could trace her reasoning and look for errors. As a result, the proportion of effort spent in Map Probing and Tracing were twice as great for the RT condition compared to the other two conditions. Presumably, this contributed to the superior content learning, as indicated by Table 4.

The metacognitive strategies practiced in the initial learning phase transferred somewhat when students had to learn the nitrogen cycle on their own. At transfer, when all students had to learn the nitrogen cycle without any special feedback or tips, the differences between conditions were much smaller. However, there was a “telling” difference that involved transitions into Map Tracing. The RT students, who had received regulation support, were twice as likely as the LT students to use Map Tracing. And, the LT students, who had taught Betty, were twice as likely to use Map Tracing as the IC students. As ratios, the differences are quite large, though in terms of absolute amount of time spent Map Tracing, they are relatively small. Nevertheless, the strategic use of Map Tracing can greatly help monitor lengthy chains of reasoning. These differences may help explain why the LT and RT treatments learned more at posttest. These students were more likely to check how their agent was reaching its conclusion, which conceivably, could have caused the superior learning.

At this point, it is only tentative that the self-regulation support in Betty affected students' learning at transfer via the learning choices they made. This HMM analysis aggregated across students and sessions within a condition. Thus, it is not possible to do statistical tests. Deriving patterns through HMM is a new approach to understanding students' metatcognitive learning choices, and it is still being developed. The main promise of analyzing these patterns is that it can help improve the design of interactive, choice-filled environments for learning. By identifying better and worse interactive patterns for learning, it should be possible to design the computer system to identify those patterns in real-time and provide adaptive prompts to (a) move students away from ineffective metacognitive patterns, and (b) encourage them to use effective patterns. Thus, an important new step will be to correlate choice patterns with specific learning outcomes, so it is possible to determine which choice patterns do indeed lead to better learning.

CONCLUSION

The chapter's leading proposal is that teaching another person, or in this case an agent, can engage productive metacognitive behaviors. This interactive metacognition can lead to better learning, and ideally, if given sufficient practice, students will eventually turn the metacognition inward.

The first empirical section demonstrated that students do take their agent's behavior as cognitive in nature, and that the agent's reasoning is correlated with the students' own knowledge. Thus, when students work with their agent, they are engaging in metacognition. It is interactive metacognition directed towards another. The second empirical section demonstrated that monitoring an agent can lead to better learning, because students internalize the agent's style of reasoning. In the final empirical section, the Teachable Agent was enhanced to include support for regulating the choices that students make to improve learning. Again, the results indicated that working with an agent led to superior content learning, especially with the extra metacognitive support in place. Moreover, students who taught an agent made a near transfer to learn a new topic several weeks later.

An analysis of students' learning choices indicated that the students who had taught agents exhibited a more varied repertoire of choices for improving their learning. They also exhibited some modest evidence of transferring these metacognitive skills by choosing to check intermediate steps within a longer chain of inference.

It is informative to contrast Betty with other technologies designed as objects-to-think-with (Turkle, 2007). Papert (1980), for example, proposed that the programming language Logo would improve children's abilities to plan. Logo involved programming the movement of a graphical "turtle" on the computer screen. Evidence did not support the claim that Logo supported planning (Pea & Kurland, 1984). One reason might be that students had to plan the behavior of the turtle, but the logical flow of the program did not resemble human planning itself. For example, the standard programming construct of a "do-loop" involves iterating through a cycle and incrementing a variable until a criterion is reached. The execution of the logic of this plan does not resemble many human versions of establishing and managing a plan. Therefore, programming in Logo is an interactive task, but it is not a task where one interacts with mental states or processes. In contrast, the way Betty reasons through causal chains is similar enough to human reasoning that programming Betty can be treated as working with her mental states. Students can internalize her cognitive structure, and eventually turn their thinking about her cognitive structures into thinking about their own.

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TABLES

Table 1. Average Number of Attributions to Success and Failure (and standard errors of the mean).

	Attributions for Success				Attributions when Failed			
Condition	Self	Agent	Both	Total	Self	Agent	Both	Total
TA Answers	.17(.12)	.27(.12)	0.0 (.0)	.44 (.16)	.54(.13)	.47(.21)	.66(.19)	1.67(.28)*
Student Answers	.53(.10)	n/a	n/a	.53(.10)	.65(.22)	n/a	n/a	.65 (.22)

Note: * $p < .05$ – comparison of condition means

Table 2. Correlations between Students' Agents and Students' Test Scores.

	Student Test Scores								
	All Questions			**TA-like Questions**			**Non-TA Questions**		
APQ Index	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3	Test 1	Test 2	Test 3
Test 1	60**	-	-	.51**	-	-	.56**	-	-
Test 2	-	.66**	-	-	.47*	-	-	.66**	-
Test 3	-	-	.34	-	-	.12	-	-	.48*

Note: ** $p < .01$; * $p < .05$. Correlations between TA-like and Non-TA questions are .47, .46, and .14 for Test 1, Test 2, and Test 3, respectively.

Table 3. Sample of Interactive Patterns and Responses by the SRL System

Regulation Goal	Pattern Description	Betty Response	Mr. Davis Response
MONITORING THROUGH EXPLANATION	**Multiple requests for Betty to give an answer but no request for explanation**	Let's see, you have asked me a lot of questions, but you have not asked for my explanations lately. Please make me explain my answers so you will know if I really understand.	Without asking Betty to explain her answers, you may not know whether she really understands the chain of events that you have been trying to teach her. Click on the Explain button to see if she explains her answer correctly.
SELF-ASSESSMENT	**Repeated quiz request but no updates have been made to the map.**	Are you sure I understand what you taught me? Please ask me some questions to make sure I got it right. I won't take the quiz otherwise. Thanks for teaching me about rivers!	You have not taught Betty anything new. Please, spend some time teaching her new links and concepts and make sure she understands by asking her questions. Then she can take the quiz again. If you need help learning new things, check the resources.
TRACKING PROGRESS	**The most recent quiz score is significantly worse than the previous**	I would really like to do better. Please check the resources, teach me, and make sure I understand by asking me questions that are on the quiz. My explanation will help you find out why I am making mistakes in my answers. Also, be sure to check out the new tips from Mr. Davis.	Betty did well on the last quiz. What happened this time? Maybe you should try rereading some of the resources and asking Betty more questions so that you can make sure she understands the material**.**
SETTING LEARNING GOALS	**Betty is asked a question that she cannot answer for the second time**	I just don't know the relationships yet, maybe we should ask Mr. Davis what we need to learn.	I've seen this kind of difficultly with teaching some of my own students in the past. You should try looking for missing link connections or links that are in the wrong direction.

Table 4. Average concept map scores at the end of the main treatment (river ecosystems) and the transfer treatment (land nitrogen cycle).

	Study Phase			
	Main Learning (1st)		Transfer for Learning (2nd)	
	Map Score		Map Score	
Condition	M	(SE)	M	(SE)
(RT) [1] Regulated Teaching	31.8 [3, 6]	(1.5)	32.6 [4]	(2.9)
(LT) [2] Learning-by-Teaching	25.8	(1.6)	31.8 [5]	(3.0)
(IC) Intelligent Coach	22.4	(1.5)	22.6	(2.9)

Note: Overall treatment means greater than IC: [1] $p < .01$; [2] $p < .05$. Post-hoc comparisons for each study phase – Greater than IC: [3] $p < .001$; [4] $p < .05$; [5] $p < .1$. Greater than LT: [6] $p < .05$

Table 5. Possible choices of activities in SRL Betty system.

Activity Name	**Student Actions**
Edit Map (M)	adding, modifying, or deleting concepts and links
Resource Access (R)	accessing the resources
Request Quiz (Q)	submitting map to take a quiz
Ask Query (A)	asking Betty or Mentor to use map to answer a question
Request Explanation (E)	asking Betty or Mentor to explain an answer to a query
Continue Explanation (C)	asking for a more detailed explanation

FIGURE CAPTIONS

Figure 1. The Teachable Agent Named Betty. The student has (a) named his agent "Bob" instead of Betty, (b) customized Bob's look, (c) taught Bob about global warming, and (d) asked Bob what happens to heat radiation if garbage increases.

Figure 2. Triple-A-Challenge Gameshow. Students log on for homework. After teaching their agents, the agents play with one another. A host asks questions of each agent. Students wager on whether they think their agent will give the right answer. The agents respond based on what the students taught them. There is a chat window so students can communicate with one another during the game.

Figure 3. Target Knowledge Organization for Global Warming Curriculum.

Figure 4. Effects of Betty versus Self. Each test included questions that depended on short, medium, or long chains of causal inference to answer correctly. With more experience across the lesson units, Betty students showed an increasing advantage for longer causal inferences. The Self condition used the concept mapping software *Inspiration* instead of Betty.

Figure 5. Adding Self-Regulated Learning to Betty's Brain. The student has submitted Betty to take a Quiz given by Mr. Davis, and the results are shown in the bottom panel. Mr. Davis and Betty provide tips and encouragement for engaging in metacognitive behaviors.

Figure 6. Transitional Probabilities between Aggregated Choice States. Each state, derived through Hidden Markov Model statistical learning, represents a pattern of choices that create a common cluster of learning activities. The numbers beside the arrows indicate the probability that students would transition from one state to another.

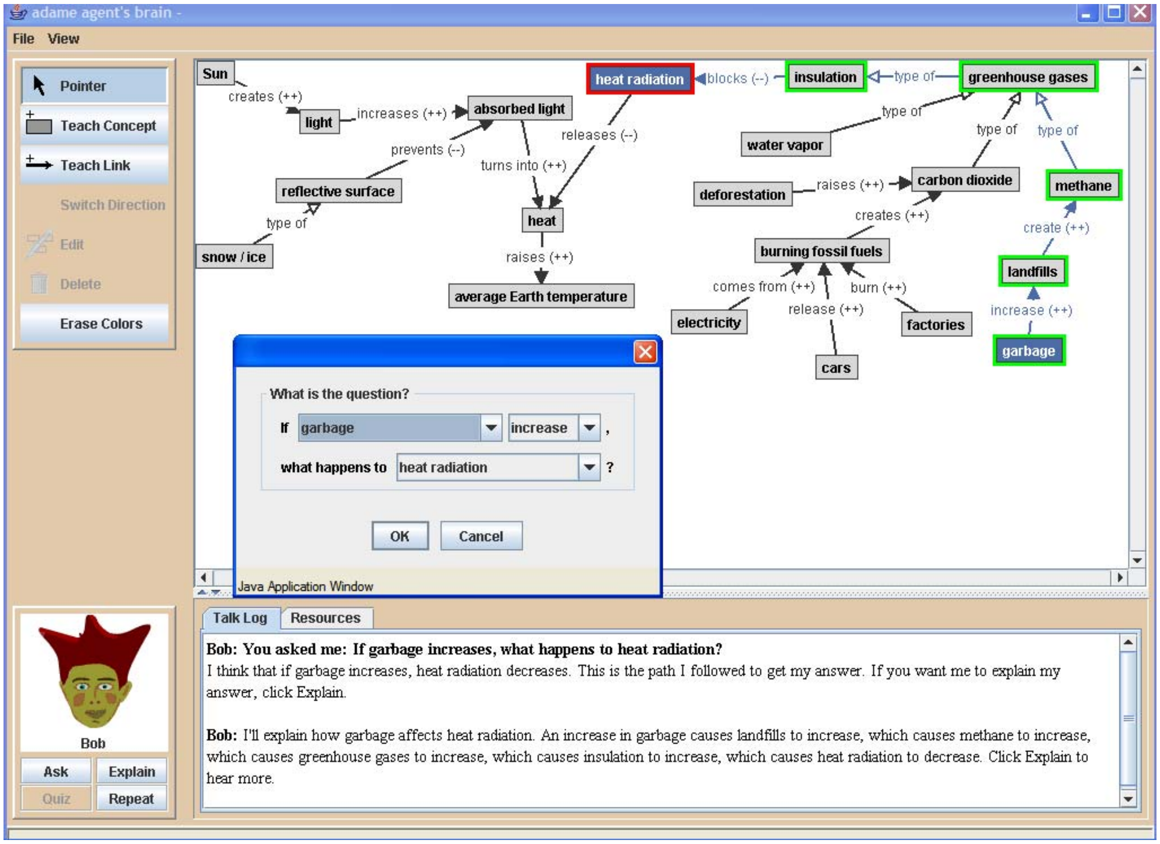

adame agent's brain -
File View
Pointer
Teach Concept
Teach Link
Switch Direction
Edit
Delete
Erase Colors
Sun
creates (++)
light
increases (++)
absorbed light
heat radiation
blocks (--)
insulation
type of
greenhouse gases
releases (--)
prevents (--)
turns into (++)
reflective surface
type of
snow / ice
heat
raises (++)
average Earth temperature
water vapor
deforestation
raises (++)
carbon dioxide
methane
creates (++)
create (++)
burning fossil fuels
landfills
comes from (++)
burn (++)
release (++)
increase (++)
electricity
factories
garbage
cars
What is the question?
If garbage increase ,
what happens to heat radiation ?
OK
Cancel
Java Application Window
Talk Log
Resources
Bob
Ask
Explain
Quiz
Repeat
Bob: You asked me: If garbage increases, what happens to heat radiation?
I think that if garbage increases, heat radiation decreases. This is the path I followed to get my answer. If you want me to explain my answer, click Explain.
Bob: I'll explain how garbage affects heat radiation. An increase in garbage causes landfills to increase, which causes methane to increase, which causes greenhouse gases to increase, which causes insulation to increase, which causes heat radiation to decrease. Click Explain to hear more.

Figure 1

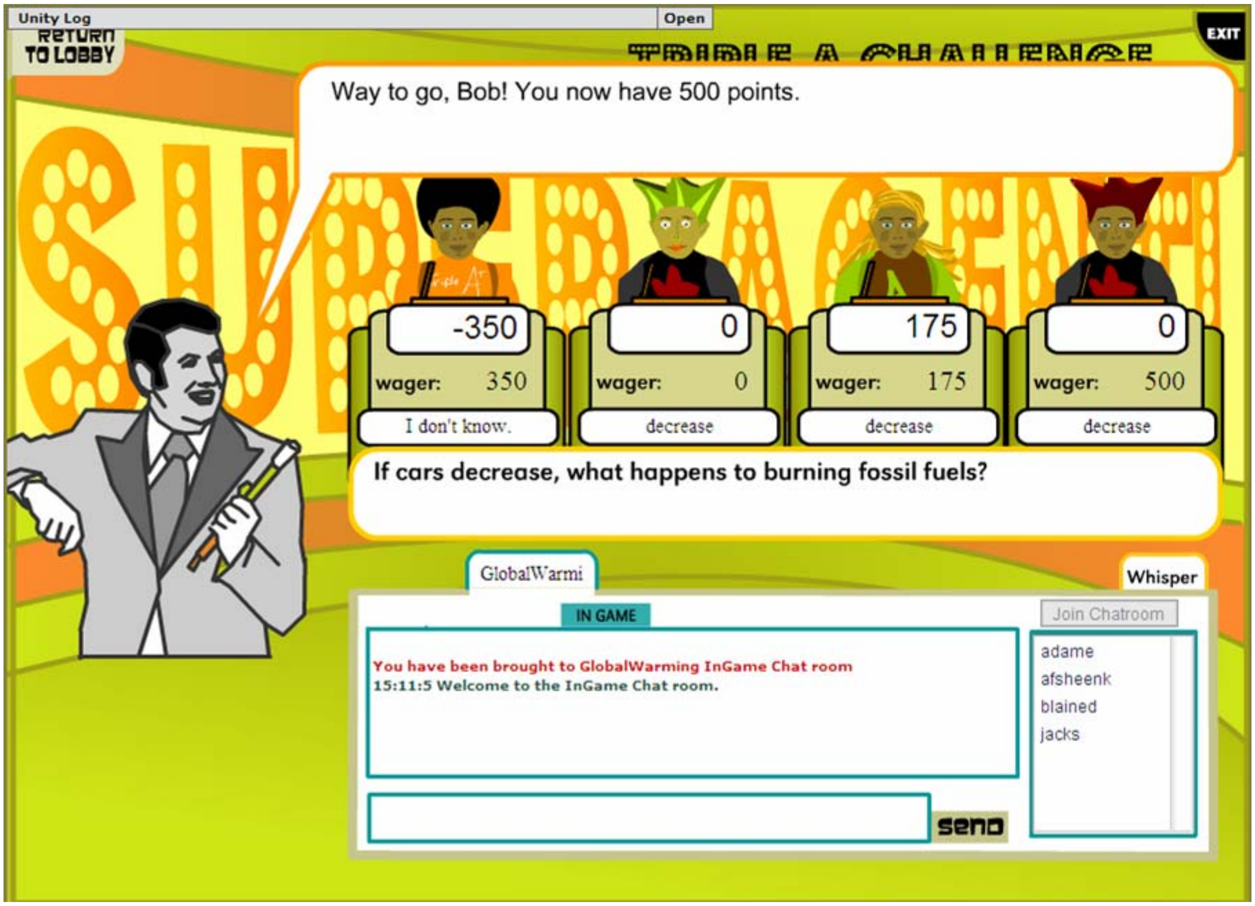

Unity Log
Open
RETURN TO LOBBY
EXIT
Way to go, Bob! You now have 500 points.
-350
wager: 350
I don't know.
0
wager: 0
decrease
175
wager: 175
decrease
0
wager: 500
decrease
If cars decrease, what happens to burning fossil fuels?
GlobalWarmi
Whisper
IN GAME
Join Chatroom
You have been brought to GlobalWarming InGame Chat room
15:11:5 Welcome to the InGame Chat room.
adame
afsheenk
blained
jacks
send

Figure 2

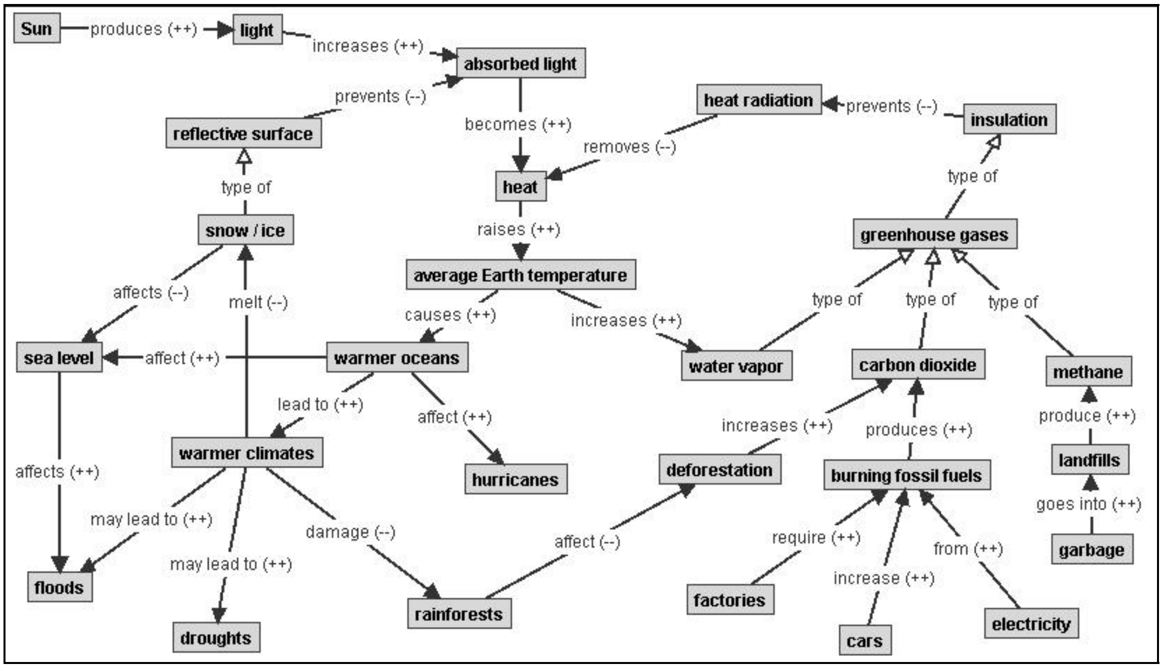
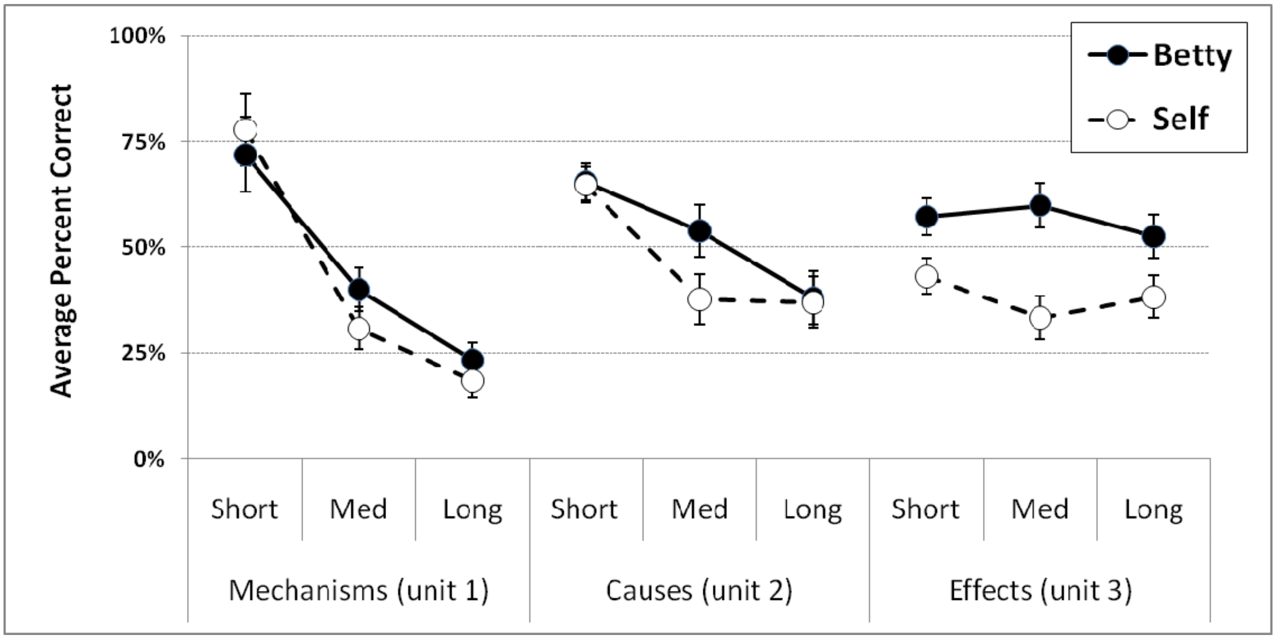

Sun
produces (++)
light
increases (++)
absorbed light
prevents (--)
reflective surface
becomes (++)
heat radiation
prevents (--)
insulation
removes (--)
heat
type of
type of
snow / ice
raises (++)
greenhouse gases
average Earth temperature
affects (--)
melt (--)
causes (++)
increases (++)
type of
type of
type of
sea level
affect (++)
warmer oceans
water vapor
carbon dioxide
methane
lead to (++)
affect (++)
increases (++)
produces (++)
produce (++)
warmer climates
hurricanes
deforestation
burning fossil fuels
landfills
affects (++)
may lead to (++)
damage (--)
affect (--)
require (++)
from (++)
goes into (++)
may lead to (++)
increase (++)
garbage
floods
rainforests
factories
electricity
droughts
cars

Figure 3.



100%
75%
50%
25%
0%
Average Percent Correct
Betty
Self
Short
Med
Long
Short
Med
Long
Short
Med
Long
Mechanisms (unit 1)
Causes (unit 2)
Effects (unit 3)

Figure 4.

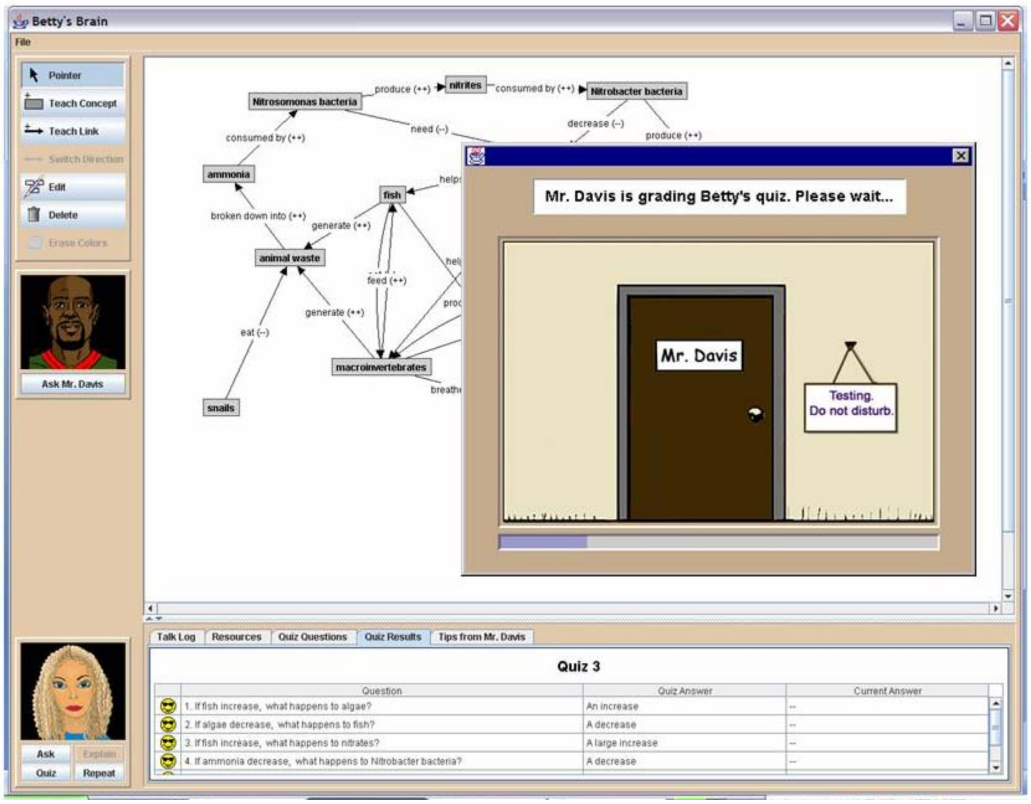

Betty's Brain
File
Pointer
Teach Concept
Teach Link
Switch Direction
Edit
Delete
Erase Colors
Ask Mr. Davis
Ask
Explain
Quiz
Repeat
Nitrosomonas bacteria
produce (++)
nitrites
consumed by (++)
Nitrobacter bacteria
need (--)
decrease (--)
produce (++)
consumed by (++)
ammonia
fish
broken down into (++)
generate (++)
animal waste
feed (++)
generate (++)
eat (--)
macroinvertebrates
snails
Mr. Davis is grading Betty's quiz. Please wait...
Mr. Davis
Testing.
Do not disturb.
Talk Log
Resources
Quiz Questions
Quiz Results
Tips from Mr. Davis
Quiz 3
Question
Quiz Answer
Current Answer
1. If fish increase, what happens to algae?
An increase
2. If algae decrease, what happens to fish?
A decrease
3. If fish increase, what happens to nitrates?
A large increase
4. If ammonia decrease, what happens to Nitrobacter bacteria?
A decrease

Figure 5.

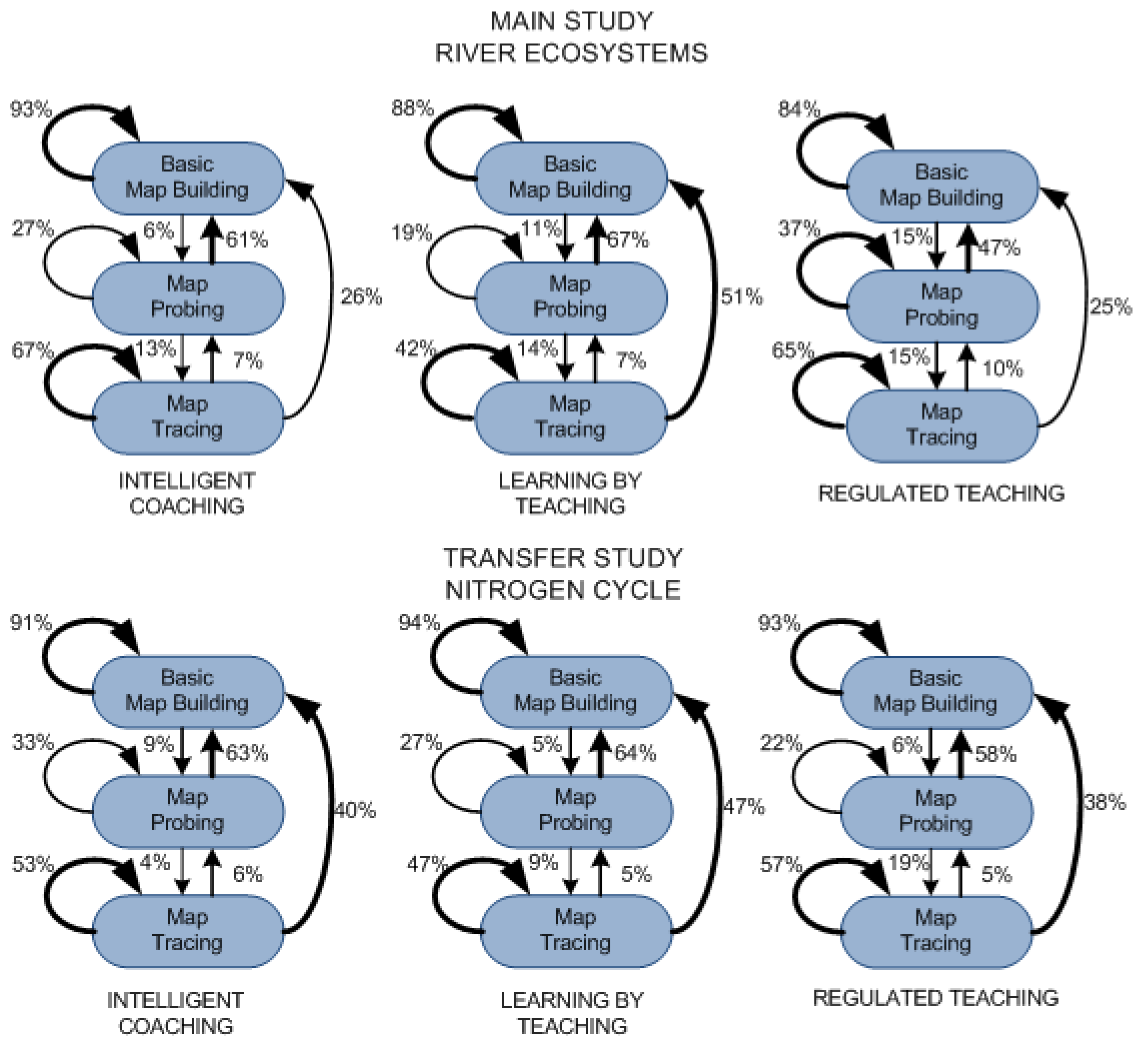

MAIN STUDY
RIVER ECOSYSTEMS
93%
Basic Map Building
27%
6%
61%
Map Probing
26%
67%
13%
7%
Map Tracing
INTELLIGENT COACHING
88%
Basic Map Building
19%
11%
67%
Map Probing
51%
42%
14%
7%
Map Tracing
LEARNING BY TEACHING
84%
Basic Map Building
37%
15%
47%
Map Probing
25%
65%
15%
10%
Map Tracing
REGULATED TEACHING
TRANSFER STUDY
NITROGEN CYCLE
91%
Basic Map Building
33%
9%
63%
Map Probing
40%
53%
4%
6%
Map Tracing
INTELLIGENT COACHING
94%
Basic Map Building
27%
5%
64%
Map Probing
47%
47%
9%
5%
Map Tracing
LEARNING BY TEACHING
93%
Basic Map Building
22%
6%
58%
Map Probing
38%
57%
19%
5%
Map Tracing
REGULATED TEACHING

Figure 6.