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A Model-Based Behavior Analysis Approach for Open-Ended Environments

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ABSTRACT

Open-ended learning environments (OELEs) are learner-centered, and they provide students with opportunities to take part in authentic and complex problem-solving tasks. These experiences may support deeper learning and the development of strategies that support future learning. However, many students struggle to succeed in such complex learning endeavors. Without proper adaptive scaffolding, these students often use system tools incorrectly and adopt suboptimal learning strategies. Developing adaptive scaffolds for students in OELEs poses significant challenges, and relatively few OELEs provide students with such support. This paper develops a *model-based approach* to interpreting and evaluating the actions students take as they learn in an OELE using a model of the cognitive and metacognitive processes that are important for completing the complex learning tasks. The model provides a means for classifying and assessing students' learning behaviors as they work on the system, and it allows the system to identify opportunities to offer adaptive scaffolds to students. An evaluation of the analysis technique is presented in the context of Betty's Brain, an OELE designed to help middle school students learn about science content.

Keywords

Open-ended learning environment, Model-based assessment, Adaptive scaffolding, Performance metrics

Introduction

Technological advances have provided researchers with affordances for designing computer-based learning environments that provide students with opportunities to take part in authentic, complex problem solving tasks. These environments, generally called open-ended learning environments (OELEs) (Clarebout & Elen, 2008; Land & Hannafin, 1996; Land, 2000; Land, Hannafin, & Oliver, 2012), are learner-centered; they provide students with a learning context and a set of tools for exploring, hypothesizing, and building solutions to problems (Bransford, Cocking, & Brown, 2000). Examples include hypermedia learning environments (e.g., Azevedo, et al., 2012; Brush & Saye, 2001), modeling and simulation environments (e.g., Leelawong & Biswas, 2008; Sengupta, et al., 2013; van Joolingen, de Jong, Lazonder, Savelsbergh, & Manlove, 2005), and narrative-centered learning environments (e.g., McQuiggan, Rowe, Lee, & Lester, 2008).

By the very nature of the choices they provide for learning and problem solving, OELEs are characterized by the opportunities they afford students to exercise metacognition (Clarebout & Elen, 2008; Land, 2000), which has been broadly defined as *thinking about one's own thinking*. It involves two synergistic components: metacognitive knowledge and metacognitive regulation (Flavell, Miller, & Miller, 2002; Schraw, Crippen, & Hartley, 2006; Winne, 2001; Zohar & Dori, 2012). Together, these describe a person's ability to explicitly set goals, establish plans for achieving goals using available resources, monitor progress toward achieving goals, and use the evaluation of progress to further regulate and improve one's effectiveness. While OELEs may vary in the particular sets of tools they provide, they often include tools for: (i) seeking and acquiring information, (ii) applying information to a problem-solving context, and (iii) assessing the quality of the constructed solution (Lajoie & Azevedo, 2006; Moreno & Mayer, 2007).

OELEs place high cognitive demands on learners (Land, 2000). To be successful, learners must understand how to execute: (i) cognitive processes for accessing and interpreting information, constructing problem solutions, and assessing constructed solutions; and (ii) metacognitive processes for coordinating the use of cognitive processes and reflecting on the outcome of solution assessments. However, research has shown that students often lack regulatory processes necessary for achieving success (Hacker & Dunloskey, 2009; Zimmerman & Schunk, 2011). Without *adaptive scaffolds*, these learners typically use tools incorrectly and adopt suboptimal learning strategies (Mayer, 2004; Land, 2000). In this article, we define adaptive scaffolds in OELEs as actions taken by the learning environment, based on its interactions with the learner, intended to support the learner in completing a task (Puntambekar & Hübscher, 2005). Such scaffolds often seek to highlight differences between desired and current learner performance and provide direction to students who are unsure of how to proceed.

Developing adaptive scaffolds for students in these complex learning environments is a difficult task for system designers (Azevedo & Hadwin, 2005; Azevedo & Jacobson, 2008); it requires developing systematic analysis techniques for diagnosing learners' needs as they relate to one or more cognitive and metacognitive processes. In OELEs, such diagnoses involve identifying and assessing learners' cognitive skill proficiency, interpreting their action sequences in terms of learning strategies, and evaluating their success in accomplishing their current tasks. The open-ended nature of OELEs further exacerbates the problem; since the environments are learner-centered, they typically do not restrict the approaches that learners take to solving their problems. Thus, interpreting and assessing students' learning behaviors is inherently complex; they may simultaneously pursue, modify, and abandon any of a large number of possible approaches to completing their tasks.

While several OELEs have been developed and used with learners, relatively few perform systematic interpretations of learners' approaches to performing their tasks in order to provide adaptive support. Instead, these systems include non-adaptive scaffolded tools (e.g., lists of sub-goals or guiding questions) designed to provide support for learners who choose to use them (Puntembekar & Hübscher, 2005). In this paper, we discuss our recent work in developing and evaluating a novel *model-based approach* for measuring and assessing the actions students take as they learn with an OELE. The approach utilizes a model of the cognitive and metacognitive processes important for completing open-ended learning tasks in an effective manner. The model, then, provides a mechanism for the system to interpret students' actions and behavior patterns in terms of these cognitive and metacognitive processes (e.g., Segedy, Kinnebrew, & Biswas, 2011), and it allows the system to identify opportunities to offer adaptive scaffolds to students. We illustrate our approach with Betty's Brain (Leelawong & Biswas, 2008; Segedy, Kinnebrew, & Biswas, 2013), an OELE designed to help middle school students learn about science.

The remainder of this paper presents Betty's Brain in more detail, including a description of the learning task and the cognitive and metacognitive model that characterizes student activities in such environments. We then use the model to derive a set of assessment metrics and apply those metrics post-hoc to data collected from a recent classroom study with Betty's Brain. The goal is to demonstrate the utility of the model-based approach in interpreting students' learning behaviors. In future work, we will incorporate our approach into the Betty's Brain system to identify opportunities for providing adaptive scaffolds to learners as they work in the system. Finally, we discuss the implications of our results for the design of feedback and adaptive scaffolding for OELEs.

Overview of Betty's Brain

Betty's Brain, shown in Figure 1, presents the task of teaching a virtual agent, Betty, about a science phenomenon (e.g., thermoregulation in mammals) by constructing a causal map that represents that phenomenon as a set of entities connected by directed links that represent causal relations. Once taught, Betty can use the map to answer causal questions and explain those answers by reasoning through chains of links (Leelawong & Biswas, 2008). The goal for students using Betty's Brain is to construct a causal map that matches a hidden, expert model of the domain.

As an OELE, Betty's Brain includes tools for acquiring information, applying that information to a problem-solving context, and assessing the quality of the constructed solution. Students acquire domain knowledge by reading a set of hypertext resources that includes descriptions of scientific processes (e.g., shivering) and information pertaining to each concept that appears in the expert map (e.g., friction). As students read, they need to identify causal relations, such as "*skeletal muscle contractions create friction in the body*." Students can then apply the learned information by adding the two entities to the causal map and creating the causal link between them (which "teaches" the information to Betty). In Betty's Brain, learners are provided with the list of concepts and link definitions are limited to the qualitative options of increase (+) and decrease (-). Students can also add textual descriptions to each link.

Learners can assess their causal map by asking Betty to answer questions (using the pop-up window shown in Figure 1) and explain her answers. To answer questions, Betty uses qualitative reasoning methods that operate through chains of links from the source concept to the target concept (Leelawong & Biswas, 2008). When Betty explains her answers, she illustrates her reasoning by simultaneously explaining her thinking (e.g., *the question said that the* *hypothalamus response increases. This causes skin contraction to increase. The increase in skin contraction causes...*) and highlighting concepts and links on the map as she mentions them.

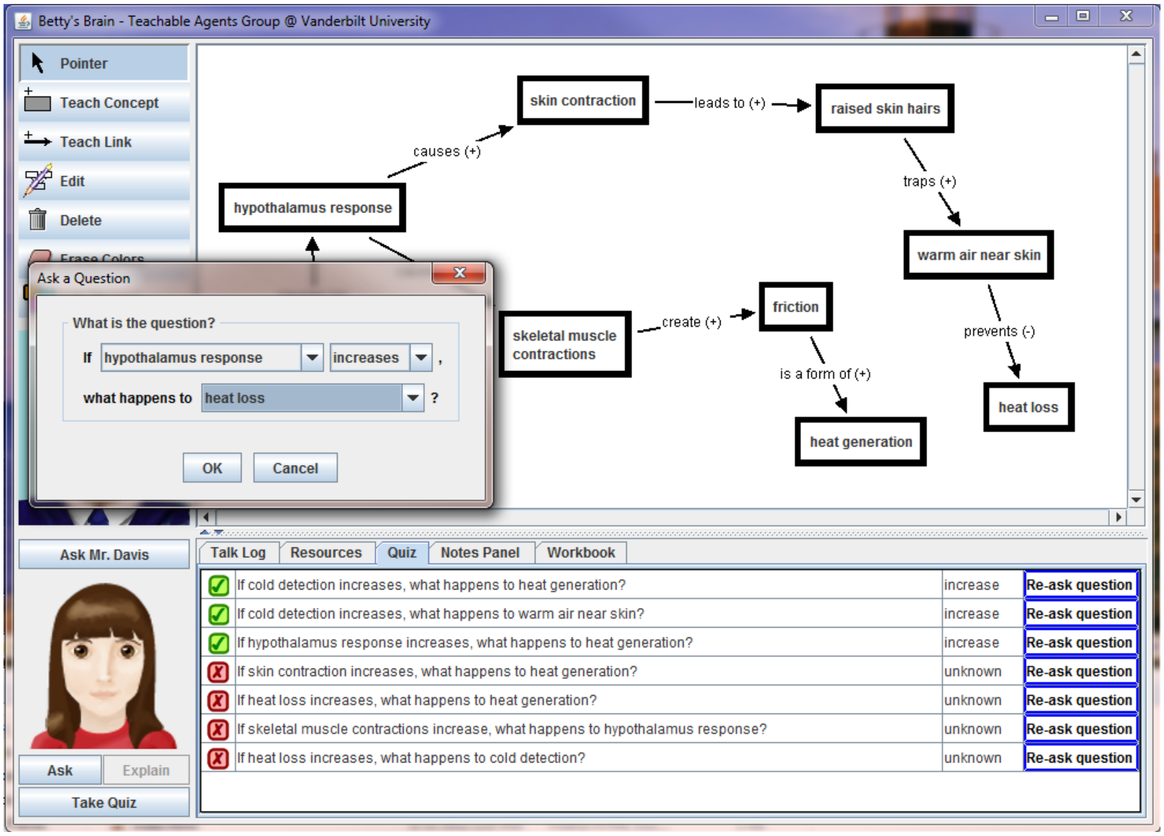


Figure 1. Betty's Brain system with query window

After Betty answers a question, learners can ask Mr. Davis, another pedagogical agent that serves as the student's mentor, to *evaluate her answer*. If Betty's answer and explanation match the expert model (i.e., in answering the question, both maps utilize the same set of causal links), then Betty's answer is correct. Note that a link's textual description is not considered during this comparison. Learners can also have Betty take *quizzes* (i.e., sets of questions). Quiz questions are selected dynamically by comparing Betty's current causal map to the expert map. Since the quiz is designed to reflect the current state of Betty's map, a set of questions is chosen (in proportion to the completeness of the map) for which Betty will generate correct answers. The rest of her quiz answers are incorrect, and they are chosen to direct the student's attention to parts of the map with missing or incorrect links. When Betty is unable to answer a question correctly, the students can use that information to discover and correct her misunderstandings. Similarly, when Betty answers a quiz question correctly, students know that the links that she used to answer that question are also correct. To help students in keeping track of which links are definitely correct, the system allows students to annotate causal links as being correct.

A model-based approach for assessing learning behaviors

As mentioned previously, properly supporting students in OELEs requires the ability to interpret their actions and behaviors. To accomplish this task systematically, we propose a novel *model-based approach* for measuring and evaluating the actions students take as they learn with an OELE. The approach utilizes a task model, developed by the authors and illustrated in Figure 2, of the cognitive and metacognitive tasks important for success in learning with OELEs (as discussed by Land, 2000 and Land & Hannafin, 1996, among others). The model specifies: (i) metacognitive tasks that learners need to engage in, (ii) cognitive processes that those tasks rely on, and (iii) tools in Betty's Brain through which learners can enact their metacognitive tasks and cognitive processes. The metacognitive tasks in the model are open-ended and general; they apply to all OELEs, and learners need to employ metacognitive regulation in order to accomplish them. In contrast, cognitive processes are procedural skills that learners need to employ properly while executing their plans, and they are specific to the OELE under study. The directed links in the model represent dependency relations. For example, solution assessment depends on learners' abilities to infer which components of the causal map are correct and which are incorrect, which in turn relies on learners' ability to interpret question grades, connect a question to the causal links that were used to answer the question, and evaluate Betty's understanding. Performing these cognitive processes requires using the system tools that allow learners to: (i) ask Betty to take quizzes and explain answers, and (ii) ask Mr. Davis to evaluate the correctness of Betty's most recent answer to a question.

The task model defines three broad classes of metacognitive tasks that learners need to engage in: (i) information seeking and acquisition, (ii) solution construction, and (iii) solution assessment. Each class of tasks involves a more specific set of metacognitive tasks, and each specific task could be accomplished by applying any of a number of metacognitive strategies. In terms of Bloom's revised taxonomy (Krathwohl, 2002), these processes involve *remembering* and *understanding* information, *analyzing* it to identify information that could be useful in constructing a solution, *applying* it to the *creation* of a solution, and then submitting the solution to an automated assessment. Learners must then *understand* and *analyze* the assessment results in order to *apply* that additional information to keeping track of correct solution components and taking steps to refine incorrect solution components. As seen in the model, information seeking and acquisition tasks depend on one's ability to identify and analyze the relevance of important information. Solution construction tasks depend on one's ability to apply information gained from both the information seeking tools and the solution assessment results to creating and refining the causal map. Finally, solution assessment tasks depend on the learner's ability to understand and interpret the results of solution assessments as actionable information that can be used to record progress and refine the current solution.

The task model provides a means for the system to interpret a student's actions in terms of the tasks and processes defined by the model (Segedy, Kinnebrew, & Biswas, 2011; Kinnebrew & Biswas, 2012). As seen in the model, each tool in Betty's Brain corresponds to multiple cognitive processes and metacognitive tasks. When a student uses one of these tools, their action is classified as being related to its associated processes and tasks. When a student accesses the resources, for example, the system interprets the action as being related to information seeking/acquisition, identifying causal relations in text, and correctly interpreting those causal relations. Similarly, when a student asks Betty to take a quiz, the action is interpreted as being related to solution assessment and evaluating Betty's understanding.

Once classified, actions are further analyzed to assess aspects of students' use of the cognitive and metacognitive processes described by the model. To assess cognitive processes, our approach judges each action taken on the system in terms of its *effectiveness*. Actions in an OELE are considered effective if they move the learner closer to their task goal, and effectiveness means something different for each class of metacognitive tasks. Effective information seeking, for example, helps students identify and acquire understanding of the specific domain content necessary for constructing an appropriate solution. Effective solution construction improves the overall quality of the solution in progress, and effective solution assessment produces and records information about the correctness and completion of the current solution. Some activities, particularly those related to information seeking, cannot always be automatically assigned an effectiveness score. However, through conversational feedback (Segedy, et al., 2013), the system could ask students to explain what they have learned from their activities, and the students' responses can serve to inform the effectiveness metrics.

By combining interpretations from multiple actions over time, the system can infer more comprehensive aspects of student behavior related to their metacognitive activities. The analysis performed in this paper uses information about how learners' actions can possibly cohere within logical plans to infer one aspect of students' metacognitive planning: *action support*. In general, action support refers to whether or not an action taken by a learner was *supported* by previous actions. For example, *information seeking actions* (e.g., reading about a causal relationship) may provide support for future *solution construction* actions (e.g., adding that causal relationship to the map). Similarly, *solution construction* actions can be supported by information produced during *solution assessment*. This latter scenario may occur in Betty's Brain when a student deletes a causal link from their map after Betty answers a question incorrectly on a quiz.

Together, classifying actions according to their related metacognitive tasks, cognitive processes, effectiveness, and action support allows the system to make decisions about when and how to scaffold learners as they work. If a learner repeatedly performs ineffective actions related to a particular cognitive process, then the system can provide support targeted toward helping the learner improve their understanding of that process and how to use it more effectively. Similarly, if a student repeatedly performs unsupported actions related to a particular metacognitive task, then the system can scaffold students' understanding of strategies for coordinating their use of the available tools in order to achieve a desired outcome.

Post-hoc analysis using model-based assessments

To illustrate the utility of the model based assessment approach, this section presents a post-hoc analysis of data from a recent classroom study conducted using Betty's Brain. The goal is to use the model based metrics defined previously to examine how learners approached their learning tasks in terms of their understanding of cognitive processes and metacognitive tasks.

Participants

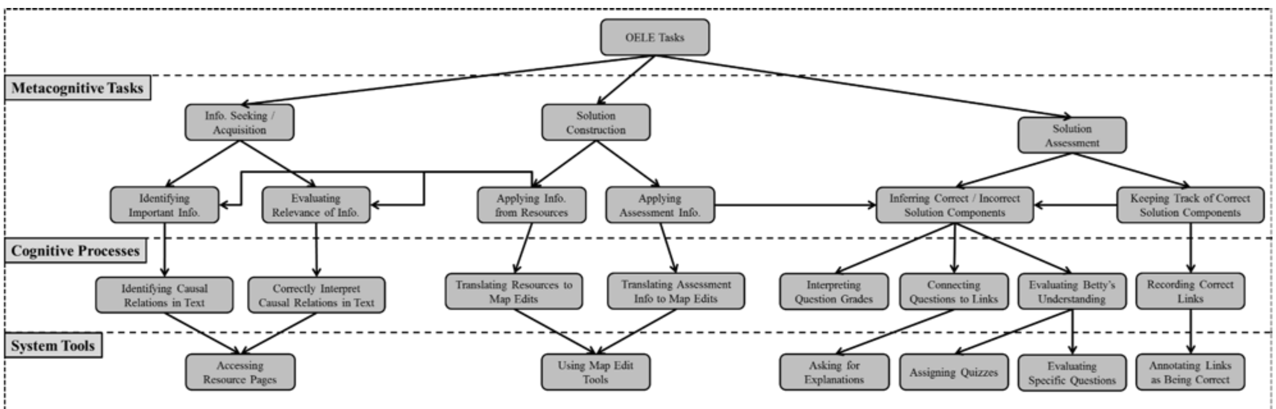


Figure 2. Cognitive and metacognitive tasks model for OELEs

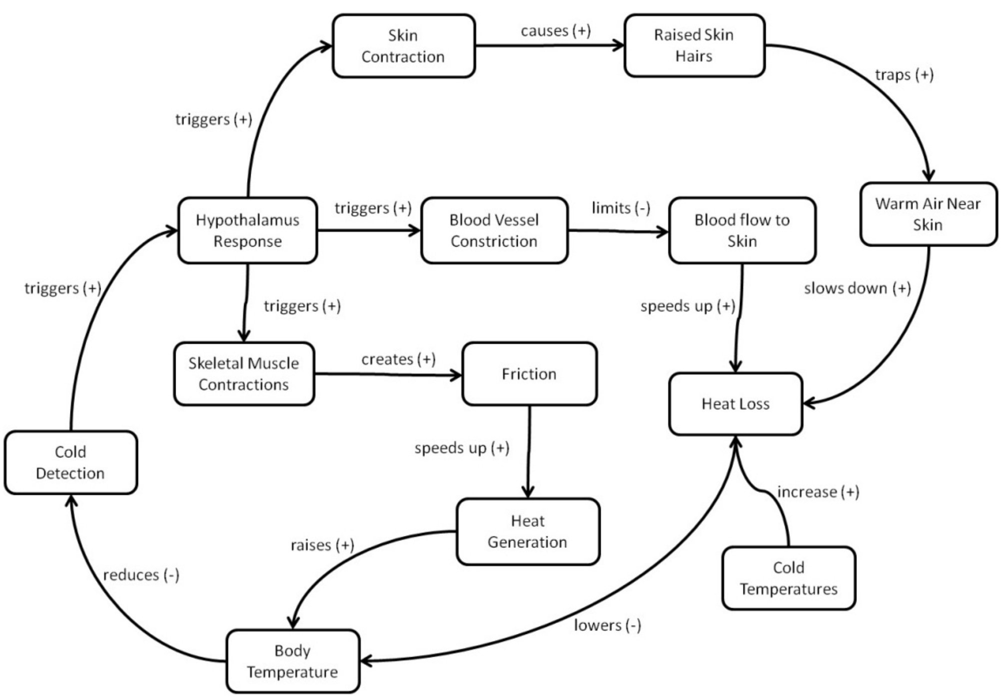


Figure 3. The Thermoregulation Expert Map

Fifty eighth grade students from three middle Tennessee science classrooms, taught by the same teacher, participated in the study. Because use of Betty's Brain relies on students' ability to independently read and understand the resources, the system is not suited to students with limited English proficiency or cognitive-behavioral problems. Therefore, while all students were encouraged to participate, data from ESL and special education students were not analyzed. Similarly, we excluded data from students who missed more than two class periods of work on the system. The final sample included data for forty students.

Topic unit and text resources

Students used Betty's Brain to learn about mammalian thermoregulation in cold temperatures. The expert map (Figure 3) contained 13 concepts and 15 links representing cold detection (cold temperatures, heat loss, body temperature, cold temperature, hypothalamus response) and three bodily responses to cold: skin contraction (skin contraction, raised skin hairs, warm air near skin, heat loss), vasoconstriction (blood vessel constriction, blood flow to skin, heat loss), and shivering (skeletal muscle contractions, friction, heat generation). The resources were organized into two introductory pages, one page covering cold detection, and three pages covering the three bodily responses to cold temperatures. Additionally, a dictionary section discussed some of the concepts, one per page. The text was 15 pages (1,981 words) with a Flesch-Kincaid reading grade level of 8.9.

Model-based assessments

Students were assessed by utilizing the model-based methodology to interpret their use of cognitive and metacognitive processes while working with Betty's Brain. Cognitive process assessments focused on students' use of solution construction (causal map edits) and solution assessment tools, the latter of which were further divided into tools for model assessment (quizzes, question evaluations, and explanations) and progress recording (annotating links as correct). These assessment metrics were chosen mainly because the log data collected in this study can be readily used to compute them.

For each set of tools associated with a particular class of metacognitive tasks, two metrics were calculated for each student: (i) *skill application*, and (ii) *effectiveness*. Skill application is defined as the average number of times a tool related to a metacognitive task was executed per minute. For example, when applying the skill application metric to solution construction, the measure was computed as the average number of causal map edits performed per minute on the system. Effectiveness was calculated as the proportion of total actions related to a particular cognitive process that moved the students closer to their task goal. For solution construction, effectiveness refers to the percentage of causal link additions, removals, and modifications (with respect to the total number of such edits) that improved the quality of Betty's causal map, where causal map quality is measured as the number of correct links minus the number of incorrect links in the map. For model assessment, effectiveness refers to the percentage of assessment actions that generated specific information about the correctness of one or more causal links. This may happen in one of several ways. First, a quiz may contain a question that Betty uses only one causal link to answer. In this case, the question's grade directly corresponds to the correctness of the causal link. Second, learners can ask Betty to explain her answer to a question that Mr. Davis has graded as correct (either via a question evaluation or a quiz). When Betty answers a question correctly, all of the links she used to answer that question are also correct. Thus, when students ask Betty to explain her answer to a correct question, they generate correctness information for each link that Betty mentions in her explanation. Finally, learners may produce correctness information for a link via a guess and check strategy in which they have Betty take a quiz, note her quiz score, make a single change to the causal map, and have Betty take a second quiz. If the second quiz is higher or lower than the first, then students infer that their recent causal map edit was correct or incorrect, respectively. Finally, for progress recording, effectiveness refers to the percentage of link annotations created that correctly describe the annotated causal link (i.e., effective link annotations only describe a link as being correct when it actually is).

To assess one aspect of students' metacognitive regulation, we calculated action support for each causal map edit. An edit was considered "supported" if one of the following conditions held: (i) students had previously accessed resource pages that discuss the concepts connected by the manipulated causal link, or (ii) the edit action removed or modified a causal link that had been previously proven incorrect via questions, question evaluations, quizzes, and explanations. A further constraint was added: an action could only support another action if both actions occurred within a ten minute window. This resulted in three scores for each student: information seeking support percentage refers to the percentage of causal map edits that were supported by condition (i); model assessment support percentage refers to the percentage of causal map edits that were supported by condition (ii); and total support percentage refers to the percentage of causal map edits that were supported by either conditions (i) or (ii).

In addition to assessing the group of students as a whole, an additional set of analyses were employed to compare students who were more and less successful in teaching Betty the correct causal model. The goal was to investigate whether or not success in the system was associated with higher levels of effectiveness and action support. Students were divided into three groups based on the quality of their causal maps at the end of the study. Students in the Low group taught Betty a map that achieved a score of 5 or below. Students in the Medium group taught Betty a map with a score of 6 to 10, and students in the High group taught Betty a map with a score of 11 to 15 (where 15 is the maximum possible score). These resulting Low, Medium, and High groups contained 18, 6, and 16 students, respectively. Because so few students fell in the Medium group, the analysis focused on comparing the skill use, effectiveness, and action support metrics between only the Low and High groups.

Procedure

The study proceeded as follows: during the first 45-minute class period, the classroom teacher introduced students to thermoregulation. During the next class period, students completed a pre-test that included questions on thermoregulation and causal reasoning. During the next two classes, the research team introduced students to the causal reasoning method used by the system and provided students with hands-on system training. Students then spent five class periods (approximately 150 minutes) using Betty's Brain with minimal intervention from the teachers and researchers. At the conclusion of the five class periods, all students took a post-test that was identical to the pre-test (pre-post test results have been reported in Kinnebrew & Biswas, 2012).

Results

Results of the group level cognitive process assessments are shown in Table 1. Students regularly engaged in information structuring and model assessment activities, editing their causal maps once every 2.28 minutes and assessing their map once every 5.15 minutes. However, students rarely made explicit records of the results of their assessment activities; they performed progress recording actions an average of once every 83.33 minutes.

Table 1. Means (and standard deviations) of cognitive process metrics

	Actions/Min	Effectiveness
Solution Construction	0.439 (0.190)	0.525 (0.113)
Model Assessment	0.194 (0.126)	0.370 (0.218)
Progress Recording	0.012 (0.033)	0.161 (0.347)

Despite engaging regularly in information structuring and model assessment behaviors, the students were not particularly effective in these endeavors. For information structuring, an average of just over half of their causal map edits improved the quality of Betty's map. This suggests that students may have struggled to understand the causal relations described in the resources; alternatively, they may have edited their maps without first consulting the resources.

Table 2. Means (and standard deviations) of model assessment metrics

	Actions/Min	Effectiveness
Question Evaluation	0.013 (0.019)	0.127 (0.280)
Explanation	0.033 (0.039)	0.060 (0.192)
Quiz	0.148 (0.111)	0.436 (0.233)

Students were even less effective in assessing Betty's understanding of the science domain. On average, just under two thirds of their model assessment actions produced no information about the correctness of one or more causal links. Moreover, these actions were largely limited to quizzes; Table 2 shows that students asked for a question evaluation once every 76.92 minutes, asked Betty to explain an answer once every 30.30 minutes, and asked Betty to take a quiz once every 6.76 minutes. This is striking, as quizzes by themselves don't often provide correctness information for a causal link. Rather, quiz questions need to be combined with Betty's explanations, which connect graded quiz answers to the sets of causal links that were used to generate those answers. It is important to note, however, that in some cases, students may have been able to infer which causal links generated an answer without requiring an explanation from Betty.

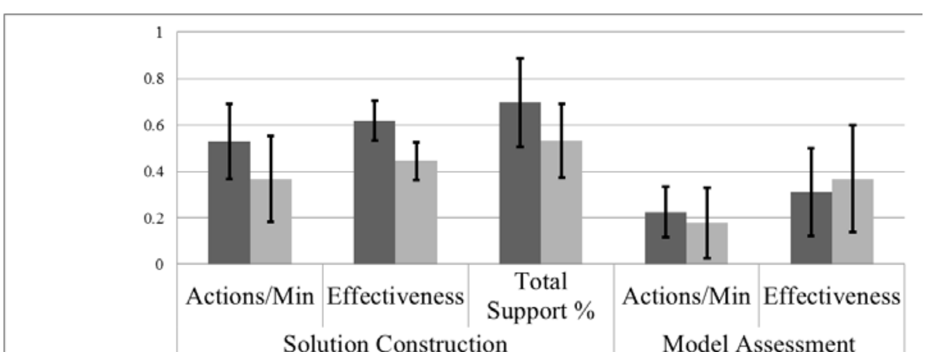
Table 3. Means (and standard deviations) of metacognitive process metrics

Information Seeking/Acquisition Support %	60.2% (18.5%)
Model Assessment Support %	0.8% (01.4%)
Total Support %	60.9% (18.3%)

Results of the group level metacognitive process assessments are shown in Table 3. Overwhelmingly, when students' causal map edits had support, that support came from their recent information seeking/acquisition actions. Just over 60% of their causal map edits were supported by recent information seeking actions, as compared to less than 1% of their causal map edits being directly supported by model assessment actions. Thus, while students regularly quizzed Betty in ways that produced information about correct and incorrect links, they rarely took advantage of that information by deleting incorrect links or annotating correct links. This suggests that students may not have understood how to use model assessment tools in order to determine which links in their causal map were correct and incorrect. They may have alternatively decided to read the resources in order to investigate incorrect quiz questions, and this reading may have supported future editing activities.

Together, these results suggest that the students in this study struggled to use Betty's Brain. More often than not, their solution construction, model assessment, and progress recording actions did not help them move toward their task goal. Moreover, almost 40% of their map edits were not supported by recent information seeking/acquisition or model assessment actions. However, despite these limitations, several students were successful (or close to successful) in teaching Betty the correct causal model. To explore the differences between students who were successful and those who were not, the cognitive and metacognitive process assessments were calculated for the High and Low student groups identified earlier. Because students rarely engaged in progress recording activities, the analysis focused only on information structuring and model assessment.

The results of the comparative analysis (Figure 4) show that the High group students more often performed actions linked to information structuring. Additionally, the High group's information structuring actions were more likely to be effective and have support from related activities. Independent samples t-tests conducted on these data showed a significant effect of group on *actions per minute*, $t(32) = 2.67$, $p = .012$, *effectiveness*, $t(32) = 5.99$, $p < .001$, and *total support percentage* $t(32) = 2.57$, $p = .015$. Figure 4 also shows that the High group performed slightly more model assessment actions than did the Low group; however, the Low group's model assessment actions were more likely to produce information about the correctness of one or more links. Independent samples t-tests conducted on these data did not reveal a significant effect of group on *actions per minute*, $t(32) = 0.98$, $p =$ n.s., or *effectiveness*, $t(32) = 0.79$, $p =$ n.s.



	Actions/Min	Effectiveness	Total Support %	Actions/Min	Effectiveness
High Mean	0.53 (0.16)	0.62 (0.09)	0.70 (0.19)	0.22 (0.11)	0.31 (0.19)
Low Mean	0.37 (0.19)	0.45 (0.08)	0.53 (0.16)	0.18 (0.15)	0.37 (0.23)

Figure 4. Means (and standard deviations) of process metrics for high and low groups

These results show that High group students' superior performances were associated with a higher rate of causal map editing and a higher proportion of effective and supported edits. However, their success was not associated with effective model assessment activities, and their map edits were rarely supported by model assessment actions. One possible interpretation is that these students were more effective than students in the Low group in identifying causal links when reading the resources. However, the low effectiveness in map editing activities combined with the extremely low number of causal map edits supported by model assessment activities in both groups implies that even students who successfully completed the learning task may have benefited from adaptive scaffolds encouraging them to carefully and systematically utilize the results of quizzes, question evaluations, and explanations.

Discussion and conclusions

In this paper, we have presented a novel *model-based approach* for analyzing the actions students take as they learn with an OELE. The approach characterizes OELEs as environments in which learners must utilize cognitive and metacognitive processes as they seek out and acquire information, apply that information to the construction of a solution, and assess the quality of their solution. We incorporated this characterization into a task model, which we then used to motivate metrics of *effectiveness* and *action support*. Effectiveness indicates whether or not learners' actions are advancing them toward their goal, and action support measures whether or not a particular action could have been motivated by information generated during a previous action. We then applied these metrics to perform a post-hoc analysis of data collected from Betty's Brain.

The analysis found that while students frequently used system tools related to solution construction and model assessment, their use of these tools was often sub-optimal. A large proportion (47.5%) of their causal map edits decreased the quality of their maps, and an even larger proportion (63.0%) of their model assessment activities did not produce information related to the correctness of one or more causal links. Further, 39.1% of their edits were not supported by recent information seeking/acquisition or model-assessment activities. Even students who were able to successfully teach Betty the correct causal map performed a large proportion of incorrect map edits (38.2%), unsupported map edits (30.3%), and ineffective model assessment actions (78.9%). The results of this analysis reveal that the students using Betty's Brain in this study might have benefited from adaptive scaffolds targeted toward helping students employ more effective strategies as they worked toward completing the learning task.

Importantly, the results of applying our model to analyze data from Betty's Brain demonstrate the utility of the analytic framework presented in this paper. By using just a subset of possible metrics for assessing students' use of cognitive and metacognitive processes, the analysis provided a detailed description of how learners in this study approached the open-ended learning task. Such information will be critical in improving the adaptive scaffolding in Betty's Brain. The model-based analyses can be executed in real-time as learners are working in Betty's Brain, and, once we incorporate them into the system, Mr. Davis will be able to leverage them in deciding how to scaffold learners.

There are a number of other OELEs that assess aspects of students' metacognition. For example, MetaTutor (Azevedo et al., 2012) is a hypermedia learning environment in which learners navigate information sources in order to achieve a pre-determined overarching learning goal (e.g., learn everything you can about the human circulatory system). To accomplish their goal, learners must employ a variety of metacognitive strategies for setting sub-goals, seeking out relevant information, and evaluating sources of information as they are encountered. The system infers learners' goals and strategies by prompting them to explicitly communicate those goals and strategies to the system as they work. For example, a learner might set a sub-goal of learning about the structure of the human heart and then select the strategy *perform a goal-directed search* from a menu of options called the *Self-Regulated Learning Palette*. As another example, recent work with Crystal Island (Sabourin, Shores, Mott, & Lester, 2012) periodically required students to indicate their affective state and a "status update." A post-hoc analysis of these self-reports found that they were predictive of student success. Thus, the authors concluded, the information provided by these reports could be used to target scaffolding and feedback to the needs of learners.

Both of these techniques require continuous self-reporting from students during learning, which differs from the approach taken in this paper. However, incorporating self-report measures into the model-based approach could lead to the ability to derive more informative assessment metrics. If learners using Betty's Brain were required to indicate their current sub-goal to the system, the system could use that additional information to select and apply a set of assessment metrics related to accomplishing that particular sub-goal. For example, if a learner has indicated that she is re-reading to make sure that she correctly constructed a causal link, then an assessment metric may test her understanding of the material related to only that link.

Future work with model-based analysis in OELEs will develop a more comprehensive set of effectiveness and support metrics with which to evaluate learners as they use Betty's Brain. Additionally, we will incorporate these metrics into Betty's Brain in order to identify opportunities for providing adaptive scaffolds to learners based on their needs. Once the decision to support students in using a particular type of cognitive or metacognitive process has been made, the pedagogical agents in the system will use the assessment metrics to drive a discussion toward identifying exactly why the learner is having trouble. Ideally, the agents will be able to provide students with the scaffolding they need to gain a better understanding of the cognitive and metacognitive processes important for managing one's own learning process. To that end, we have developed a set of tutorial activities for students to practice some skills important for success in teaching Betty, such as identifying causal relations from reading materials and identifying relevant link correctness information from quizzes (Segedy, Biswas, Blackstock, & Jenkins, 2013). Hopefully, this support will lead to an increase in students' effectiveness in learning with Betty's Brain.

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