

# Supporting Student Learning using Conversational Agents in a Teachable Agent Environment

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**Abstract:** This paper presents a design experiment and case study of a four-fold approach to agent feedback in Betty’s Brain, an open-ended Teachable Agent learning environment that requires students to gain familiarity with and employ a number of cognitive and metacognitive skills to achieve success in their learning and teaching tasks. Our approach is based on designing feedback according to the principles of goal-alignment, context-relevancy, integrated cognitive and metacognitive support, and a conversational approach to feedback delivery. We tested this feedback approach on 43 8<sup>th</sup>-grade students, and our findings illustrate that: (1) students conversational choices provide valuable insight into their current mental state, (2) despite the help, some students struggled to learn using the system. These results prompt us to make new recommendations for continued development of feedback in complex, open-ended learning environments.

## Introduction

For a number of years, our group has used the learning-by-teaching paradigm to design an open-ended learning environment called Betty’s Brain (Leelawong and Biswas, 2008). Students teach a virtual agent, named Betty, about science topics by reading source material and constructing a causal map (Figure 1) that represents relevant science phenomena as a set of entities and causal relations (links) among them. Once taught, Betty (the Teachable Agent) can use her map to answer causal questions (*e.g.*, *if cold detection increases, what effect does it have on an animal’s blood vessel constriction?*) and explain those answers by reasoning through chains of links (Leelawong and Biswas, 2008). The goal for (human) students using Betty’s Brain is to teach Betty a causal map that matches a hidden, expert model of the domain. To gauge their progress towards this goal, students can make Betty take quizzes, which are sets of questions created and graded by a virtual mentor agent named Mr. Davis. Mr. Davis compares Betty’s answers with those generated by the expert model and assigns grades accordingly. Thus, when Betty is unable to answer quiz questions correctly, the (human) students can use that information to discover Betty’s (and their own) misunderstandings and correct them by modifying the causal map.

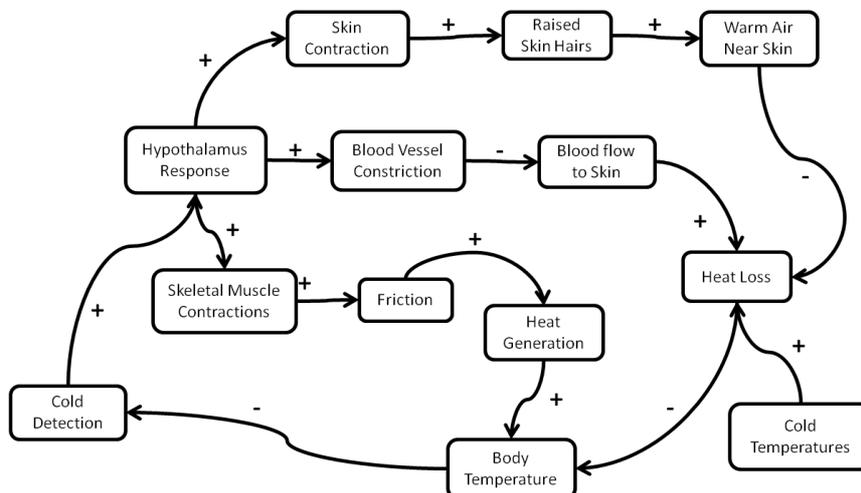


Figure 1. An example causal map on body temperature regulation

More generally, Betty’s Brain is an open-ended and choice-rich learning environment that presents students with the complex task of carefully reading about and modeling science phenomena. To achieve success in the environment, students must employ a number of cognitive and metacognitive skills (see Figure 2). At the cognitive level, they need to identify important information from the reading materials, represent that information in the causal map format, and use questions and quizzes to check how Betty performs. At the metacognitive level, they need to decide when and how to acquire information, build and modify the causal map they are creating to teach Betty, check Betty’s progress, reflect on their own understanding of the science knowledge, and seek help or feedback from Mr. Davis. One important goal of working with learners in such an open-ended

environment is developing their abilities to independently regulate their learning process in *preparation for future learning* (Bransford and Schwartz, 1999). Such preparation, through the development of metacognitive and self-regulatory skills, is important for developing effective learners in the classroom and beyond (e.g., Zimmerman, 2001). However, previous studies have shown that middle school students do not have well-developed independent learning strategies; and as novices they often adopt suboptimal trial-and-error methods when they encounter difficult, open-ended, and exploratory learning tasks (Azevedo, 2005).

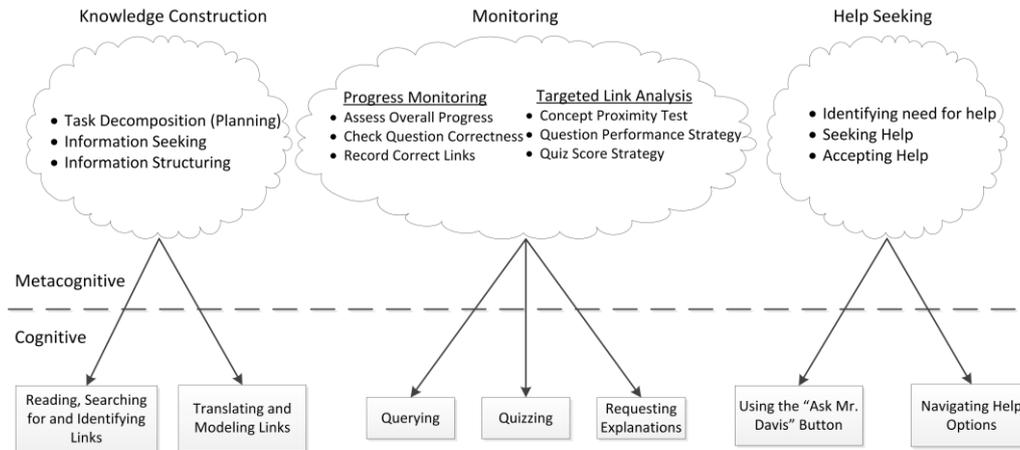


Figure 2. Cognitive skills and metacognitive strategies important for success in Betty's Brain

In our system, both Betty and Mr. Davis provide dialogue-based feedback to promote effective metacognitive strategies for knowledge construction, monitoring, and help-seeking. However, the agents intentionally avoid providing students with direct answers (e.g., a correct causal link), and they never require users to make a specific, "correct" next step. Instead, Betty's interactions illustrate her metacognitive awareness. On the other hand, Mr. Davis proposes metacognitive strategies or prompts for reflection as feedback in response to student difficulties and unproductive behaviors. Our hypothesis is that using this form of agent dialogue and feedback to help students adopt productive metacognitive strategies will be more effective in preparing them for future learning than providing domain-specific answers and hints.

Testing the effectiveness of the agents' strategy feedback in previous classroom studies, however, has produced limited success. For example, an analysis of video-taped sessions of students using Betty's Brain during a classroom study in 2009 revealed that 77% of the feedback statements delivered by agents appeared to be ignored by students, and students rarely pursued help from Mr. Davis. Additional analysis demonstrated that many students lacked understanding of the cognitive skills required for teaching Betty, and this promoted unproductive learning behaviors. These analyses lead us to hypothesize that students need more explicit dialogue-based support. Thus, we re-designed our agent dialogue around four principles: *goal-alignment*, *context-relevancy*, *integrating cognitive and metacognitive support*, and a *conversational approach to feedback delivery*. We report a design experiment and case study (Brown, 1992) in an 8<sup>th</sup> grade science classroom, where we investigate the effectiveness of our feedback approach by analyzing students' performance, learning behaviors, and conversations with Mr. Davis. Like other design experiments, our goals are two-fold: (1) analyze experimental results to study the effectiveness of the current approach, and (2) use the results to develop and refine our theory of feedback for complex, open-ended learning environments.

### A Four-Fold Approach to Feedback Design

In order to address the various student difficulties mentioned previously, we modified our dialogue design to comply with four design principles: *goal-alignment*, *context-relevancy*, *integrated cognitive and metacognitive support*, and a *conversational approach to feedback delivery*. The goal-alignment principle dictates that feedback needs to explicitly align with student goals. In other words, the agents should not only suggest strategies, but should also explain how students can employ them. The context-relevancy principle advocates that feedback be specific to the learner's current situation, so that the learner can more easily apply the recommended strategy. The third principle states that the feedback should provide support for all of the skills and strategies that students need to master (e.g., by providing worked examples and explanations). Finally, the fourth principle relates to the mechanism by which feedback is delivered, and it prescribes back-and-forth *conversations* with multiple exchanges that engage learners in social interactions with the agent.

We use conversation trees (Adams, 2009) to represent dialogue and feedback in Betty's Brain. In a conversation tree, nodes represent a computer character's dialogue and the branches represent conversational choices available to the user after a response. This structure avoids the complexity of natural language pro-

cessing, and the alternation of agent dialogue and student responses allows a joint negotiation of both the conversation’s direction and follow-up activities.

## Experimental Study and Results

To explore the effectiveness of our new feedback framework, we implemented several conversational structures in Betty’s Brain. We then ran a study on 43 8<sup>th</sup>-grade students, who were asked to learn about thermoregulation using the system. In analyzing the data from this study, we divide students into high- and low-performing groups (with 18 students in each group), as determined by scoring the causal maps they created to teach Betty<sup>1</sup>, dropping a small set of students in the middle. In this study, the maximum possible causal map score was 15. The mean and standard deviation of the high group’s map score was 14.6 and 0.77, respectively. Conversely, students in the low group achieved map scores with a mean and standard deviation of 2.8 and 1.59, respectively. Considering the big difference in the success of these two groups, we conducted a series of analyses to understand the differences in students’ learning behaviors and dialogue choices.

As a first step, we analyze aggregate student behavior by employing hidden Markov models (HMMs) with previously developed methods to provide a concise representation of student learning strategies and behaviors (Biswas *et al.*, 2010). HMMs include a set of states and probabilistic transitions (*i.e.*, more likely transitions are assigned higher probabilities) between those states. Like a student’s mental processes, the states of an HMM are hidden, meaning that they cannot be directly observed, but they produce observable output corresponding to student actions in the learning environment.

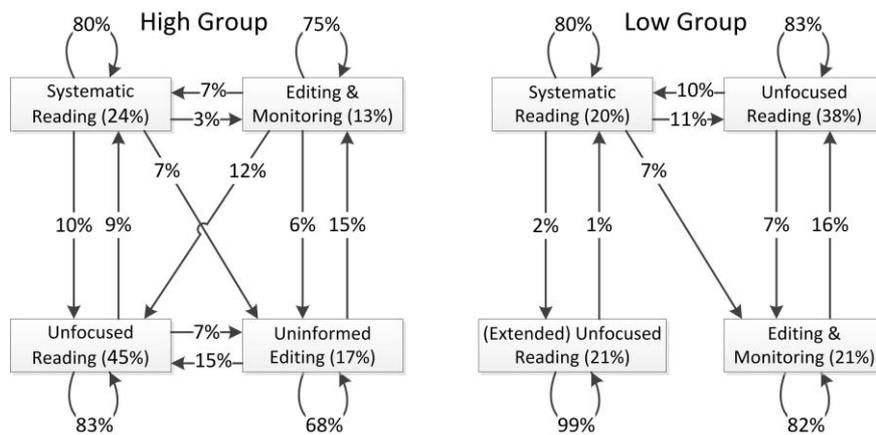


Figure 3. Learning behavior models for high- and low-performance groups

We derive aggregate HMMs from a group of students’ learning activity traces. We first characterize each student activity as one of five, qualitatively distinct actions: reading the science materials, editing the causal map, querying Betty, probing Betty’s understanding by asking her to explain her answers, and making Betty take a quiz. However, this abstraction of the raw activity trace logs removes useful contextual information (*e.g.*, *was the student’s query related to a recent map edit?*). To maintain a balance between simplicity and interpretability, we use context information to label each action by its *relevance* to immediately preceding actions (Biswas *et al.*, 2010). Using this relevance metric, we split each categorized action (other than quizzes, for which this characterization does not apply) into two distinct actions: high relevance, meaning the action is related to at least two of the previous three actions, and low relevance otherwise.

Figure 3 illustrates the two HMMs derived from the high- and low-performing student activity traces. The percent value listed within each state is the frequency of that state occurring relative to the other states in the model. Using the interpretation methods detailed in (Biswas *et al.*, 2010), we interpreted these states as representing: (1) *Systematic Reading* – students are reading material that has high relevance to previous actions; (2) *Unfocused Reading* – students are reading material that has low relevance to previous actions; (3) *Editing and Monitoring* – students are monitoring the correctness of their causal maps using queries and quizzes and are making both high and low relevance edits to their causal map; and (4) *Uninformed Editing* – students are making low-relevance edits to their map, possibly indicating the use of guessing strategies (*e.g.*, trial-and-error).

In comparing the derived HMMs for the high- and low-performance groups, the largest difference is that the uninformed editing activities are split into a separate state (Uninformed Editing) in the high group rather than being combined with the informed editing activities in the Editing & Monitoring state as in the low group. This suggests a more strategic use of edits in the high group when in the editing and monitoring state, *i.e.*, their

<sup>1</sup> Causal map scores provide a measure of task performance and were calculated by subtracting the number of incorrect map links from the number of correct map links.

edit actions are more relevant to their recent monitoring activities. In contrast, the low group’s editing activities seem to be less focused, suggesting greater reliance on trial-and-error approaches. Another important difference in focus and systematic strategy use between the two groups is the additional (Extended) Unfocused Reading state in the low group HMM. The extremely high self-loop probability (99%) in this state indicates that upon entering the state, a student would generally continue performing unfocused reading activities for an extended period of time. Further, the low group HMM indicates a greater overall reliance on unfocused reading (59% expected state occurrence, combining the two Unfocused Reading states) compared to the high group (45%).

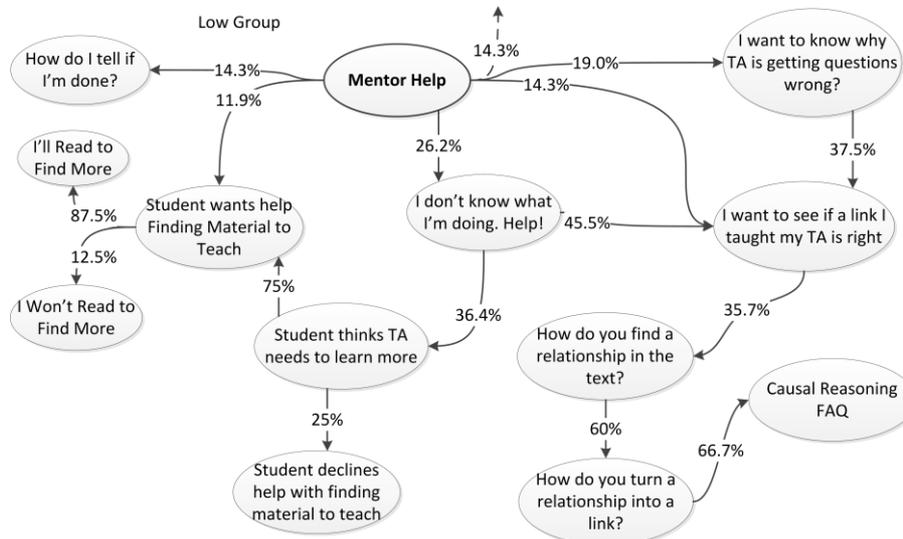


Figure 4. A flowchart showing how the low group moved through the help conversations.

Overall, these results suggest that students in the high group adopted more effective learning strategies that combined directed reading, checking, and focused map building. Together, these effective strategies could explain their success in map building and teaching efforts. On the other hand, low-performing students were more likely to apply what we characterize as suboptimal learning strategies, such as unfocused reading and uninformed editing. However, these results do not directly elucidate how the cognitive and metacognitive dialogue with agents affected student learning behaviors. It could be that the high-performing group was better able to understand and use the dialogue than the low group. Another possibility is that the high group was more willing to engage in dialogue with the agents or knew when to ask for help. To investigate these issues, we analyze how students used the on-demand help feature provided by Mr. Davis.

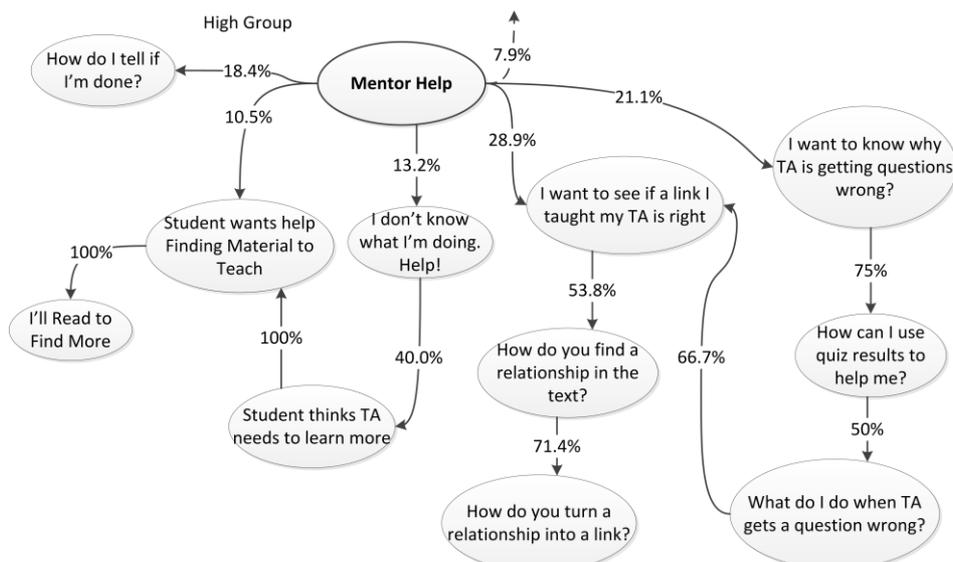


Figure 5. A flowchart showing how the high group moved through the help conversations.

At any time, students could ask Mr. Davis for help. He responded by asking learners where they needed help, providing five possible options, illustrated in Figures 4 and 5. To understand students’ help-seeking be-

havior, we investigated students' choices of help topic and the level of detail to which they pursued that topic using clarifying questions. Figures 4 and 5 illustrate the help dialogue differences between the low and high groups. All conversations started in the **Mentor Help** state when the student requested help from Mr. Davis, and the arrows show the percentage of times students chose each subsequent help option. For example, in the low group, 14.3% of the times that a student asked Mr. Davis for help, that student wanted to know how to determine if they were done teaching Betty. The dashed line from the mentor help state represents the proportion of times students requested help but chose to end the conversation instead of asking a specific question.

Examining the flowcharts in Figures 4 and 5 reveals some interesting differences in how the two groups used the help system. First, students in the low group were much more likely to end the help conversation immediately after the mentor asked them what kind of help they needed (14.3% versus 7.9% for the high group). Second, students in the low group were also much more likely to tell Mr. Davis that they didn't know what to do next (26.2% vs. 13.2% for the high group). These observations suggest that students in the low group were struggling to determine relevant learning activities while teaching Betty.

## Discussion and Conclusions

In this paper, we presented the results of a design experiment to explore the effectiveness of a four-fold approach to designing agent dialogue that supports independent learning in a complex, open-ended science learning environment. This approach calls for feedback based on the principles of *goal-alignment*, *context-relevancy*, *integrated cognitive and metacognitive support*, and a *conversational approach to feedback delivery*. In this paper, we mainly report on the effects of the conversational approach to feedback.

The data analysis and case studies provided insight into the feedback's impact on the students' ability to achieve success in teaching Betty. We found that students' conversational choices contain information about their understanding of the learning task, as students from the low group were more likely to indicate that they were unsure of how to proceed. By analyzing differences between the stronger and weaker performers, we also concluded that low performers were not provided sufficient support to succeed at the task. They were less able to utilize the help system, and they spent much of their time performing unfocused reading and uninformed editing. While the feedback designed for this study was much more explicit than in previous studies, many students were still unable to achieve success. This suggests that the four-fold approach to feedback may not be enough to help all learners. Based on our analysis of videos from a previous study, we have learned that students' dismissal of agent dialogue often implies that they are unable or unwilling to understand the feedback's meaning and how it applies to their task. An important direction for future work is to continue to refine our feedback principles to better support students as they face these and similar difficulties. One of our goals is to extend our HMM approach of modeling student learning behavior in order to detect more detailed patterns of weaker student behavior during learning and provide appropriate feedback. Currently, we are refining our conceptual framework for feedback and incorporating these improvements in preparation for our next experiment.

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