What Information Does this Question Convey? Leveraging Help-Seeking Behavior for Improved Modeling in a Simulation-Based Intelligent Tutor

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Abstract

Asking questions is an important help-seeking behavior that many intelligent tutoring systems (ITSs) do not use. Allowing learners to ask questions of an ITS has the potential to improve learning and also to provide a new source of input for ITSs' internal models. In this paper, the different ways an ITS can input questions, answer them, and then use them to update its student model are discussed. A taxonomy of question response for model-based learning environments is proposed, and inquiry modeling, a new framework to let learners ask questions of an ITS with more freedom than existing methods, is described. Inquiry modeling is being developed and tested in a popular military training simulation, the DVTE-CAN.

1. INTRODUCTION

Personalized tutoring can be a highly effective pedagogical tool. Students who learn from a dedicated human tutor can perform, on average, in the top two percent of students who spend the same amount of time learning the material in a classroom setting [Bloom 1984]. Although it is often too resource-intensive to offer one-on-one human-led training to more than a few students, tools such as intelligent tutoring systems (ITSs) promise to provide efficient personalized instruction to a much wider audience.

ITSs are pedagogical computer systems that teach or train learners in highly personalized ways. Even in complex simulated environments, ITSs have reduced instructor workload and improved training effectiveness [Jensen et al. 2007; Cannon-Bowers 2008]. However, despite their many successes, ITSs are still less effective than one-on-one, human-led instruction [Corbett 2001; Porayska-Pomsta et al. 2008]. If a future ITS can become as capable as a human tutor, then it might open up the advantages of one-on-one training to many more trainees.

To find out why ITSs have not yet equaled the performance of human tutors, researchers should examine the differences between the experience of learning from an expert human tutor and the experience of learning from an ITS. One difference is the availability and quality of student-initiated interactions. When students learn from a human tutor, they are able to ask any question that comes to mind. Students often ask a human tutor many questions in the course of one session [Graesser and Person 1994; Soler 2002; Mercier and Frederiksen 2008]. As this paper describes, typical ITSs possess limited capacities to support such interactions.

1.1. Intelligent Tutoring Systems

ITSs are educational software systems characterized by their *artificial intelligence* and *adaptive capabilities*. These computer tutors present individually tailored content, track performance, offer feedback, and guide the instructional process. ITSs' artificial intelligence determines what content to teach and how to teach it, assesses learners' performance, and diagnoses the reasons for that performance. ITSs' adaptive capabilities let them recognize, store, and then respond to student inputs such as performance, behaviors, and individual characteristics.

Classically, ITSs consist of a task environment, domain knowledge module, learner model, and pedagogical module [Corbett et al. 1997]. This paper mainly focuses on the learner model, a component which researchers also refer to as a student model or user model. A learner model represents everything an ITS "knows" about a learner or group of learners. Depending on the ITS, different learner models may include diverse information such as demographic data, estimates of competence, or even reconstructions of mental events [VanLehn 1988]. An ITS's learner model is key to its personalized tutoring.

1.2. Help Seeking

Seeking help represents an important part of learning, and willingness to ask for help correlates with other adaptive cognitive and metacognitive strategies [Karabenick and Knapp 1991]. On the other hand, not seeking help when it is needed can have disastrous consequences, even for very capable people [Sandoval and Lee 2006].

When a learner asks a question of an expert human tutor—the pedagogical gold standard—that help-seeking act is actually the culmination of a process first described by Nelson-Le Gall [1981]. The steps of the help-seeking process are quoted below:

1. Become aware of a need for help.
2. Decide to seek help.
3. Identify potential helper(s).
4. Use strategies to elicit help.
5. Evaluate the help-seeking episode.

Effectively negotiating the process of asking a question is a metacognitive skill at which untrained learners often perform poorly [e.g., Aleven and Koedinger 2000; Walonoski and Heffernan 2006]. For example, the first step of the process could break down if the learner does not notice a misconception [VanLehn et al. 2003], or one of the later steps could be blocked by hesitation to interrupt, belief that help will not be effective, or other social and affective factors [Newman 1998]. Breakdowns of the help-seeking process can cause learners to ask few or ineffective questions, even when working one-on-one with human tutors [Graesser and Person 1994].

Although students may find it difficult to ask effective questions, engaging in successful help-seeking leads to better learning [e.g., Webb et al. 2006]. Fortunately, instructors can teach, or otherwise encourage, better question-asking [Marbach-Ad and Sokolove 2000; Harper et al. 2003]. In fact, at least one ITS directly teaches effective help use in many domains [Roll et al. 2005]. Future ITSs could build on this trend to encourage help-seeking even more than human tutors do, for example by mitigating the interpersonal factors that raise a barrier to asking questions.

1.3. Role of This Paper

This paper draws on interdisciplinary research to build a taxonomy of the ways that questions can be used in ITSs and other model-based learning environments. Existing research suggests ways learners can ask questions of an ITS, ways the ITS can answer them, and ways the ITS can interpret the questions as input for its learner model. This research offers useful perspectives and starting points for ITS experts to explore help seeking.

This paper will focus on questions that are instrumental to learning, as opposed to questions that derive from in-character behavior or are otherwise inherent to the narrative of a scenario. The distinction is necessary because when a learner takes on a role within an instructional simulation that role may normally require question-asking behaviors. For example, a doctor in a simulated emergency room may ask questions to gather new information from a simulated patient [Domeshek 2008], but the questions are designed to explore the current situation, not to learn new material. ITSs already commonly handle such in-character questions, in the same way that they process and respond to other behaviors that they are programmed to train. The purpose of such questions differs from questions designed for help-seeking, and they might not be created through the Nelson-Le Gall help-seeking process discussed above. This paper focuses on ways an ITS could allow questions that are instrumental to learning and make them as useful to the learner model as in-character questions already are.

Based on the promise of more effectively handling questions, this paper goes on to introduce *inquiry modeling*. Inquiry modeling refers to the ability of an ITS to answer learners' questions and, importantly, to use them in updating its learner model. Several existing ITSs incorporate aspects of this functionality.

As part of the Next-generation Expeditionary Warfare Intelligent Training (NEW-IT) project, the authors are exploring the impact, efficacy, and characteristics of inquiry modeling in the context of a successful military scenario-based training system, the Deployable Virtual Training Environment Combined Arms Network (DVTE-CAN) [Bailey and Armstrong 2002]. The authors plan to add inquiry modeling to the DVTE-CAN and then compare it against traditional, performance-only trainee models.

The rest of this paper is organized as follows. Section 2 describes ways interactive learning environments can interact with learner questions. Section 3 introduces inquiry modeling and describes a plan for its development and operationalization, including future research directions. Section 4 presents a brief conclusion.

2. A MODELING-CENTERED TAXONOMY

This section proposes a novel taxonomy of question support for computer-based learning environments. The taxonomy contains three orthogonal dimensions that ITS practitioners, in contrast to human tutors, trainers, and pedagogical experts, must consider:

1. *Input freedom* describes the constraints the ITS places on learners' questions with its user interface.
2. *Model integration* describes how learners' questions update the ITS's internal model.
3. *Response characteristics* describe how the ITS answers learners' questions.

2.1. Input Freedom

In order to leverage learner questions in an ITS, the system must first allow the learner to ask questions. The system interface can give learners freedom to ask whatever they want, or it can impose constraints on their questions. The learners' freedom to choose their own questions has an impact on the information the questions can convey to the model, on the ease of implementation, and on the user experience.

Figure 1 lists some ways learners may request help in different ITSs. The interfaces are located along a continuum from *constrained* to *free*. As an ITS's question interface moves higher in the freedom dimension, learners become more able to ask any question they please.

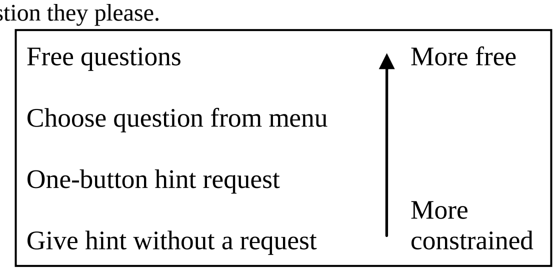

Figure 1. Freedom. Different question interfaces may have an impact on the information questions contain and on user experience, including cognitive load.

2.1.1. Effects on Questions' Information Content

Freedom impacts how questions can update a learner model. With more constrained interfaces, questions convey less information about learners' mental states. For example, in a common constrained interface, a trainee can click a hint button within an ITS, which may then use that act to infer that the trainee is unsure either about what to do next or about how to do it. However, from the hint request alone the system cannot conclude which difficulty the learner has, or what obstacle is causing the difficulty. The ITS must instead consult the learner model to surmise a best estimate of what has gone wrong.

In contrast, if an ITS can accept a question chosen from among several options on a menu, then the learner's question choice more precisely pinpoints the problem. Rather than consulting the learner model to get more information about the help request, the ITS derives the information directly from the learner and, if properly equipped, it can actually update the learner model with the new information. In this way, the freer interface raises the upper bound on the amount of information the ITS can infer from a question.

The interface with the highest degree of freedom shown in Figure 1 is labeled "Free questions." This category includes natural-language typed, handwritten, and spoken questions. Because such a free question interface does not limit what the learner can ask, the learner's questions have the potential to contain even more information. Whether a particular ITS has sufficient capability to understand natural language, and its learner model has enough detail to take advantage of the expanded information, will determine whether the ITS is able to realize the potential of its freer interface and extract more information from each question.

For completeness, the input freedom scale includes a zero point to describe ITSs that offer hints based upon student performance or other factors in the learner model. Help in such an ITS must be entirely driven by the learner model, with no learner initiative, and as a consequence the learner model cannot glean new information from the help episode. Although giving help without waiting for a request can be important, this mode of interaction can hardly be termed a question and will not be discussed in this paper.

2.1.2. Effects on Learning

There are several ways that the freedom to ask questions might affect an ITSs teaching or training effectiveness, and the freest question-asking interfaces may not necessarily produce the optimal results. For instance, more constrained question-asking interfaces may put less strain on learners' cognitive workload, and they may help teach learners more effective help-seeking behavior. Further, such interfaces can be more readily created by ITS developers.

Asking a question is a mental task that may compete for cognitive resources that a learner could otherwise use to accomplish schema acquisition and automation—i.e., learning [Sweller 1988; Aleven et al. 2006]. In particular, framing a question and expressing it in words require mental effort [Newman 1998]. More constrained interfaces, like clicking a single button or choosing a question from only a few options, remove the need for these intermediate steps and might help to lighten the cognitive load.

In addition, the ability to suggest questions may also let more constrained interfaces support the first step of Nelson-Le Gall's [1981] model, which is to identify the need to ask a question. For example, an ITS with a question menu could detect a misconception in the learner and populate its menu with suggestions that point out the contradiction [Johnson et al. 2009]. This ability would be less natural, though not impossible, with completely free help request inputs.

Placing constraints on a learner's help-seeking process also has the potential to add scaffolding [Clarebout and Elen 2006] to help train a skill that is known to be difficult for many learners. For example, presenting a menu of questions could give an ITS the opportunity to suggest deeper or more effective questions than the learner might have thought of alone. In this way a more constrained interface could act as a role model for how to ask good questions, as advocated by Newman [1998].

Finally, there may be practical issues associated with greater interface freedom in a simulated environment. One ITS that required trainees to type during a simulated infantry task found that the trainees could not both type and keep up with events in the simulator [Jensen et al. 2007]. Allowing speech input instead of typing may address this issue in some environments. In environments that also limit trainees' speech, the simulator may even need to pause or otherwise accommodate the distraction of entering a question.

As described in this section, greater input freedom may come with higher costs both for implementers and for learners, while constraining inputs can give learners valuable scaffolding. These considerations may have led some ITS designers in the past to avoid free question interfaces. However, the previous section suggested that more free interfaces give more potential to infer data about the learner from each question, while imposing constraints lowers the upper bound on the amount of available information. Effectively integrating the most possible question information into the learner model may require more freedom to ask questions than traditional ITSs have previously supported.

2.2. Model Integration

The questions a learner asks a tutor contain a wealth of information about that learner. The information can be explicit in the meaning of the question, but it can also be implicit in the timing, frequency, and context of the question, i.e., what has been said before, what the learner is working on, or what is going on at the moment in a simulation. *Model integration* describes the ways an ITS infers information from questions to update its learner model.

Figure 2 suggests the different learner model components that an ITS can adapt based on the questions learners ask it. The questions potentially contain information about each learner's *traits and states* or *misconceptions*. While specific misconceptions depend on the problem domain, the figure also shows some examples of domain-agnostic traits and states that researchers have differentiated with learner questions.

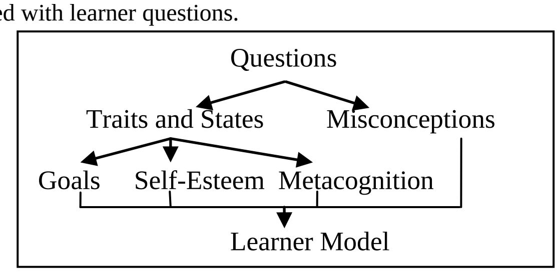

Figure 2. Model integration. Questions can update both global and domain-specific learner model data.

Help-seeking researchers have used question features such as frequency, generality, and depth to identify several psychological traits and states in learners. Goal orientation is one example. Learners can act from motivation to master new material, to outperform expectations, or merely to avoid underperforming [Harackiewicz et al. 2002]. Learners' question-asking behavior can help reveal these goals [Ryan and Pintrich 1997]. In the same way, the questions learners ask can provide insight into their global self-esteem [Karabenick and Knapp 1991]. And since the act of asking questions requires monitoring and attempting to self-regulate knowledge, it represents a metacognitive skill [Aleven et al. 2006]. Therefore, the tutor can make inferences about learners' reflection and other abilities based on how effectively they use questions.

Many other traits and states may be possible to infer. For example, several ITSs have the ability to infer boredom by detecting certain behavior patterns. However, fewer ITSs attempt to detect frustration and floundering [Lane 2006]. Certainly something as simple as a text box to type invective into would give learners an easy channel to signal their frustration to the ITS.

In addition to traits and states, questions can also give valuable clues to learners' misconceptions. Especially in complex simulations, trainees' actions alone can sometimes give too little information to diagnose the root cause of poor performance [Kodaganallur et al. 2006]. In such cases, any questions a trainee asks may provide crucial evidence to help identify a misconception.

2.3. Response Characteristics

An important part of using trainee questions is answering them. Intuitively, an ITS that allows questions but fails to answer in a timely fashion is unlikely to elicit effective help-seeking behavior. Directly answering questions benefits learners by letting them verify beliefs, address knowledge deficits, and establish common ground [Graesser and Person 1994]. Furthermore, any ability of the ITS to answer some questions independently represents reduced workload for human instructors.

Question answers are one class of pedagogical intervention, and this paper will not review all of the timing and content recommendations that are already well studied in the context of ITS hints and help [e.g., Aleven et al. 2003]. However, two considerations inspired by studies of human question answering are also relevant to ITSs that answer questions: the social role the ITS plays when it answers a question, and role of the answer in an ongoing dialogue.

2.3.1. Social Role

Many ITSs offer hints and help to learners, so their relationship with learners is similar to that of a human teacher or mentor. Likewise, answering questions is a task that places an ITS in a specific relationship to the learner.

This section describes three social roles an ITS can play when answering a learner's question. These roles are broad categories loosely based on Moore's [1989] taxonomy of interactions in effective learning. The roles, drawn as a Venn diagram in Figure 3, are *authority*, *peer*, and *reference*. This section describes how answering questions in different ways might place an ITS in different social roles and thus change how learners ask questions.

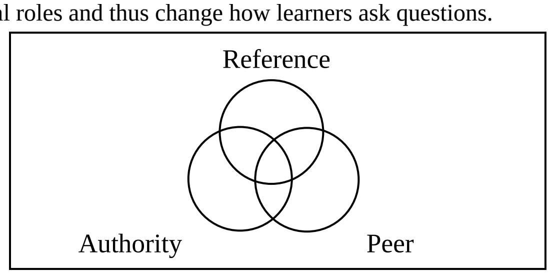

Figure 3. Response roles. An ITS can take on one or more social roles when responding to questions.

One possible source of question answers is an authority, such as a teacher, trainer, or other expert. A second help source is a peer, such as another trainee participating in the same simulation. Thirdly, answers can come in the form of reference material that is not mediated by a person, such as a manual.

The role an ITS presents when responding to a question can change learners' estimates of what to ask and how to ask their questions. For example, a learner may include more explanation when asking a peer a question than when asking an expert [Bromme et al. 2001]. When addressing an authority, learners may use more polite phrasing [Puustinen et al. 2009].

There is precedent for ITSs to purposefully play a social role. For example, researchers study relationship manipulation explicitly when they equip an ITS with a pedagogical agent, a virtual person who helps learners in ways a teacher [e.g., Conati and Zhou 2004] or peer learner [e.g., Burleson 2006] might. These social agents can both improve performance and engender a positive attitude about learning [Lester et al. 1997].

ITSs very often offer learners hints and corrections. Since the ITS possesses (presumably correct) knowledge and instructs the learner, these interactions often place the ITS in the *authority* role. Alternatively, an ITS could also give hints to the learner as a *peer* by couching them in more deferential terms. Authorities and peers have beliefs about what a learner knows or can do. When they answer questions, they can empathize with frustration, share in satisfaction, or even act as role models [Burleson 2006].

In the context of ITSs answering questions, the choice to play the role of an authority or peer is an interesting one. When interacting with humans, learners sometimes avoid asking questions to avoid displaying ignorance or, in the case of asking a peer, incurring a debt [Fisher et al. 1982]. This suggests that peer or authority responses from an ITS may trigger some of the same reluctance, and has led to research aimed at mitigating such negative affect [e.g., Wang and Johnson 2008].

Even when they are playing the role of an authority or peer most ITSs do not hide the fact that they are programs, a fact which might have the side effect of making ITSs less socially threatening than human teachers. On the other hand, a less typical mechanism for answering questions as an authority or peer might actually be relaying learners' questions to a human. Such a method might help in situations where the ITS fails to parse and "understand" some questions. A hypothetical ITS that used humans to answer questions would share some characteristics with collaborative learning or distance learning, but it would additionally have the potential to interpret some questions as learner model inputs.

When an ITS's answers do not display any intentionality at all, learners may perceive it not as help but as a *reference*. Reference responses are characterized by their appearance of generality and lack of adaptation to the situation at hand. Even though an ITS might be personalizing reference responses internally, the learner does not perceive the answer to be mediated by an intentional agent, even an artificial one. An example is presenting a textbook page that is relevant to a learner's question [e.g., Graesser et al. 2004]. Because reference-type responses might sidestep questions of reconstructing natural language and context, they might be easier to implement. However, learners may not use reference help as much as personalized help [Aleven and Koedinger 2000; Graesser et al. 2004], or their questions might devolve into typical web queries, i.e., lists of noun phrases [Broder 2002].

2.3.2. Dialogue Context

In ITSs, question answering can take place with varying amounts of dialogue context. An ITS can answer each question separately from previous questions, can engage in an ongoing dialog, or can even create a multi-agent conversation involving more than one artificial personality or real human. The choice of dialogue context has the potential to change the learner's experience, for example by affecting perceived realism or feeling of presence [Chertoff et al. 2008].

Dialogue management, including the task of remembering what has been said before, is a topic of ongoing research. One field using dialogue context is that of conversational agents or chatbots. Although widely used general-purpose chatbots simplify the dialogue task by processing each conversational line separately [Shah 2006], it is possible to maintain long-term context by limiting the discussion domain [Allen et al. 1994]. Interactive question answering systems also limit their domain so as to answer questions in natural language [e.g., Varges et al. 2008]. A second method for an

ITS to answer questions with context awareness might be to constrain dialogue options to a tree, like a telephone menu system does. As for multi-agent conversations, a step in that direction is an agent that can answer questions on a multi-user forum by referring back to previous posts [Feng et al. 2006].

2.3.3. Other Pedagogical Concerns

Finally, in addition to social role and dialogue context, answering questions also involves considerations that are familiar to most ITS practitioners from designing hints and other help vectors. For example, answers can be immediate or delayed [Butler and Winne 1995]. There are pedagogical considerations of which problems to focus on when there are more than one [Anderson 1993]. Also, answers need the right timing and detail level to avoid distraction or cognitive overload [Koedinger and Aleven 2007]. These question response considerations have parallels in existing research on ITS intervention design. As mentioned, such issues have received substantive attention in the mainstream ITS literature and will not be further outlined in this paper. Interested readers should see [e.g., Aleven et al. 2003] for more details.

2.4. Existing ITSs

Many ITSs that have a detailed student model, such as cognitive tutors, are able to customize the help they offer learners, such as hints about the next step in a problem. Typically, the ITS displays help either with no request, such as when the student makes a mistake, or with a constrained help request, such as clicking a hint button [e.g., Koedinger and Aleven 2007]. In some ITSs, the students' hint usage updates the student model, for example decreasing the comprehension estimate [e.g., Ainsworth and Grimshaw 2004] or even acting as evidence of cheating [e.g., Baker et al. 2008]. In contrast to inquiry modeling, these ITSs model learners based at most on the existence and timing of help requests. However, a few ITSs do offer more free question interfaces or draw richer information from help-seeking interactions.

STEVE [Rickel and Johnson 1999] is a simulator-based ITS that teaches tasks such as maintaining an air compressor. A speech recognition interface lets the trainee ask three types of questions: "What is the next step," "How do I do that," or "Why?" The questions are answered by a Soar module that plans in real time how to complete the domain task. However, the ITS does not use the extra information from its freer question interface to better model trainees. Further, STEVE's effect on learning has not been reported, nor has the extent to which trainees actually ask the ITS questions.

Autotutor [Graesser et al. 2004; Graesser et al. 1999] is an ITS that teaches physics. Autotutor uses a text-based or spoken interface to carry on a dialogue with the student, making student utterances the behaviors the ITS evaluates. Since the student can freely type or speak his or her part of the dialog, students can ask the ITS questions to learn about the material. The ITS answers questions in a reference role by performing pattern-matching on students' questions to categorize their type and content, searching a text for related sections, and presenting the top five matching sections for the student to read. The ITS does not use the students' questions for modeling or for changing the dialogue, and Autotutor's authors state that students do not often ask questions of the ITS. Studies have shown Autotutor has a positive effect on learning, especially on deep understanding of the topic [Graesser et al. 2004].

Quantum Simulations, Inc. is a commercial enterprise building ITSs that teach subjects such as math, chemistry, and accounting [Johnson et al. 2009]. Their tutors constrain student progress through each problem by referencing a framework of steps that must be followed. As the student works on each step, an internal production rule set models the student's thinking and selects questions the student might have, displaying them in a menu. Subject-matter experts write the questions and accompanying short answers. One such ITS has demonstrated a positive effect on learning, and anecdotal evidence suggests that students in that experiment did use the question facility [Johnson et al. 2009].

METTLE [Domeshek 2008] is an ITS that trains medical doctors in disease diagnosis. Trainees interact with the training environment mainly by asking questions of simulated patients and doctors, so question responses are in the peer role. The trainee can freely speak or type questions to simulated agents, and since these questions are in-character behaviors they always update the learner model. On the other hand, METTLE's facility for asking questions that are instrumental to learning, rather than in-character behaviors, is limited to choosing from a menu of "What next", "How," and "Why?" These questions are answered outside the simulator context and do not update the ITS's trainee model.

3. INQUIRY MODELING

Although a few existing ITSs let learners ask questions, clear differences remain between learning with an ITS and learning from a human. Humans still have more flexibility to teach in complex domains, answer a wider range of questions with more helpful answers, and are better able to estimate learners' abilities and characteristics based on their questions among other things.

An ITS that can answer questions and use them to improve modeling might be better able to teach and train. A new framework for using questions in this way is *inquiry modeling*. Inquiry modeling is now undergoing its first development and evaluation as a prototype add-on to the military training simulator DVTE-CAN.

3.1. Framework for Inquiry Modeling

Figure 4 gives a high-level view of the processes inquiry modeling will add to an existing ITS, which is being incorporated into DVTE-CAN.

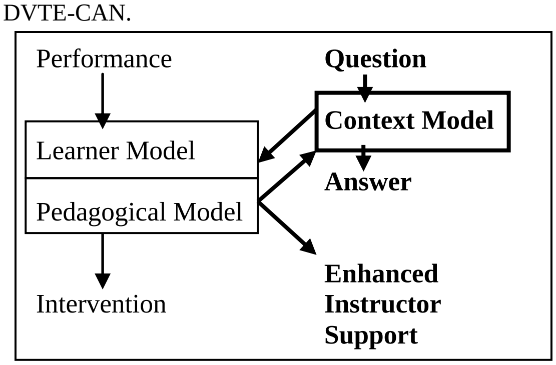

Figure 4. An ITS architecture, with new question support structure shown in bold. The new *context model* transforms questions into learner model inputs and mediates answers from the ITS.

The heart of an ITS is its ability to adapt to an individual learner. Typically, an ITS will assess a learner's performance and intervene as necessary. The ITS uses the performance as evidence to update its estimates of states, traits, and misconceptions in the learner model, and then the pedagogical model uses these data to determine what material to present or help to offer.

Inquiry modeling provides a new potential source of input to the learner model, in the form of questions from the learner. As discussed above, these questions should not only serve as input, but the ITS should answer the questions. Further, in systems that keep human instructors in the loop, the learner's questions can also enhance the feedback the ITS gives instructors.

The information a question can provide to a learner model is not limited to its content. The context of the question may also convey information. Context includes information about what the learner is working on, what has recently happened in the simulation, and what previous questions and answers might form an ongoing dialogue. What constitutes important context will be different for every ITS. For more free interfaces, context may even be necessary just to determine the meaning of a natural-language question. But even without natural language, the ITS will need to monitor question context to draw the most possible data from learner questions into the learner model. The ITS's context model is key, because without it the ITS will be unable to translate learner questions, especially ones with high input freedom, into learner model inputs [Graesser et al. 2004].

The context at any given moment also plays a part in determining the proper response to a question. When a question triggers an answer or other intervention from the pedagogical module, the response can be filtered through the context model to make it more natural or otherwise more effective. For example, answers can refer back to previous dialogue or use pronouns correctly. If the ITS is used in a training simulation and the context model contains information about what is happening in the simulation, then the context could change answers' timing and detail to reduce interruptions at critical moments.

As shown in Figure 4, there is another valuable product of inquiry modeling besides answering learners' questions and updating the learner model. The questions learners ask can also give instructors more detailed feedback. Since the questions are already discretized into usable features for the ITS's learner model, it is easy to aggregate them and collect trends. Even with questions as free as natural-language help requests, the ITS can present instructors with valuable information about how students are relating to the material.

3.2. Project Evaluations

The initial inquiry modeling project will include the following experiments to make concrete the value of the new framework and the focus on modeling with questions.

1. Do trainee questions, as elicited in a think-aloud protocol, include extra information about the trainees not available from their performance alone?
2. If so, then does the extra information from questions help make the learner model more accurate?
3. Finally, if learner models become more accurate, are the differences between inquiry-informed models and performance-only models sufficient to recommend different training interventions?

If test results confirm positive hypotheses under these formative measures, the project will proceed to test inquiry modeling's effect on trainees' learning as compared to the simulator without inquiry modeling. This summative experiment represents a high standard because many factors contribute to trainees' learning.

3.3. Research Directions

This project or others will need to address a wealth of research issues surrounding inquiry modeling both for ITSs in general and particularly for ITSs integrated with complex simulated environments. This section suggests some of the many interesting questions that inquiry modeling might raise.

Inquiry modeling is likely to be more effective when learners ask more and better questions of the ITS. What are the best strategies to encourage questions? For example, help seeking is mediated by social factors. Can manipulating an ITS's social role address these factors? Will there be a need to balance the benefits of allowing questions without social punishment against the potential for help abuse?

In a training simulation, other considerations may also affect how learners ask questions. As one example, an ITS may need to answer questions based not on ground truth but on knowledge available to the trainee, a complex task in itself. But will there be a chilling effect on willingness to ask questions if the ITS gives a deliberately wrong answer?

Finally, many of the theoretical issues in the ITS and simulation-based training fields bear directly on inquiry modeling. Researchers might debate the best data structures and model types to support integrating questions with learner models, create new tools to help subject-matter experts generate possible questions and answers, or even explore automatic answer generation for some classes of questions.

The many research opportunities surrounding inquiry modeling suggest that the method holds great promise for any interested researchers.

4. CONCLUSION

Questions play an important role in teaching and training by human experts, so it may be that ITSs could teach or train better if they answered learners' questions. Answering questions can help learners fill knowledge gaps and exercise metacognition. The questions can also let the ITS know more about learners and better model their states, traits, and misconceptions.

There are many ways ITSs can incorporate learner questions. ITSs can give learners more or less freedom to ask questions, respond in different ways, and use aspects of the questions for learner modeling. This paper introduced inquiry modeling, a framework for using learner questions more effectively than any previous ITS has.

A new, funded project will add inquiry modeling to a widely used military training simulation. A series of experiments in this project will provide support for the hypothesis that, as with human tutors, the inquiry modeling technique for ITSs can improve modeling and increase learning.

There are many more questions surrounding inquiry modeling and how best to realize the benefits of answering learners' questions. Researchers studying intelligent tutoring and modeling and simulation should investigate some of the many possibilities and interesting questions of inquiry modeling.

References

Ainsworth, S., and S. Grimshaw. 2004. "Evaluating the Redeem Authoring Tool: Can Teachers Create Effective Learning Environments?" *International Journal of Artificial Intelligence in Education* 14 (3):279–312.

Aleven, Vincent, and Kenneth R. Koedinger. 2000. "Limitations of Student Control: Do Students Know When They Need Help?" In the Proceedings of the 5th International Conference on Intelligent Tutoring Systems, (Montréal, Canada, June 19–23, 2000). Springer Verlag, Berlin, 292–303.

Aleven, Vincent, B. McLaren, I. Roll, and Kenneth R. Koedinger. 2006. "Toward Meta-Cognitive Tutoring: A Model of Help Seeking with a Cognitive Tutor." *International Journal of Artificial Intelligence in Education* 16 (2):101–128.

Aleven, Vincent, E. Stahl, S. Schworm, F. Fischer, and R. Wallace. 2003. "Help Seeking and Help Design in Interactive Learning Environments." *Review of Educational Research* 73 (3):277–320.

Allen, J. F., L. K. Schubert, G. Ferguson, P. Heeman, C. H. Hwang, T. Kato, M. Light, N. G. Martin, B. W. Miller, and M. Poesio. 1994. "The Trains Project: A Case Study in Defining a Conversational Planning Agent." Rochester, NY: University of Rochester.

Anderson, John Robert. 1993. *Rules of the Mind*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Bailey, M. P., and R. Armstrong. 2002. "The Deployable Virtual Training Environment." In the Proceedings of the Interservice/Industry Training, Simulation, and Education Conference, (Orlando, FL). National Training and Simulation Association.

Baker, R. S. J., Albert T. Corbett, and Vincent Aleven. 2008. "More Accurate Student Modeling through Contextual Estimation of Slip and Guess Probabilities in Bayesian Knowledge Tracing." In the Proceedings of the 9th International Conference on Intelligent Tutoring Systems, (Montreal, Canada, June 23–27, 2008). Springer, Berlin / Heidelberg, 406–415.

Bloom, B. S. 1984. "The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring." *Educational Researcher* 13 (6):4–16.

Broder, Andrei. 2002. "A Taxonomy of Web Search." *ACM SIGIR Forum* 36 (2):3–10.

Bromme, R., R. Rambow, and M. Nückles. 2001. "Expertise and Estimating What Other People Know: The Influence of Professional Experience and Type of Knowledge." *Journal of Experimental Psychology: Applied* 7 (4):317–330.

Burleson, Winslow. 2006. "Affective Learning Companions: Strategies for Empathetic Agents with Real-Time Multimodal Affective Sensing to Foster Meta-Cognitive and Meta-Affective Approaches to Learning, Motivation, and Perseverance." PhD Thesis, MIT Media Laboratory, Massachusetts Institute of Technology, Cambridge, MA.

Butler, D. L., and P. H. Winne. 1995. "Feedback and Self-Regulated Learning: A Theoretical Synthesis." *Review of Educational Research* 65 (3):245–281.

Cannon-Bowers, J. A. 2008. "Recent Advances in Scenario-Based Training for Medical Education." *Current opinion in anaesthesiology* 21 (6):784–789.

Chertoff, D. B., S. L. Schatz, R. McDaniel, and C. A. Bowers. 2008. "Improving Presence Theory through Experiential Design." *Presence: Teleoperators and Virtual Environments* 17 (4):405–413.

Clarebout, G., and J. Elen. 2006. "Tool Use in Computer-Based Learning Environments: Towards a Research Framework." *Computers in Human Behavior* 22 (3):389–411.

Conati, Cristina, and Xiaohong Zhou. 2004. "Building and Evaluating an Intelligent Pedagogical Agent to Improve the Effectiveness of an Educational Game." In the Proceedings of the 9th International Conference on Intelligent User Interfaces, (Funchal, Madeira, Portugal). ACM, New York, NY, 6–13.

Corbett, Albert T. 2001. "Cognitive Computer Tutors: Solving the Two-Sigma Problem." In the Proceedings of the 8th International Conference on User Modeling). Springer-Verlag, Berlin / Heidelberg, 137–147.

Corbett, Albert T., Kenneth R. Koedinger, and John Robert Anderson. 1997. "Intelligent Tutoring Systems." In *Handbook of Human-Computer Interaction*, edited by M. Helander, T. K. Landauer and P. Prabhu. New York, NY: Elsevier Science.

Domeshek, E. A. 2008. "Medical Emergency Team Tutored Learning Environment." San Mateo, CA: Stottler Henke Associates, Inc.

Feng, D., E. Shaw, J. Kim, and E. Hovy. 2006. "An Intelligent Discussion-Bot for Answering Student Queries in Threaded Discussions." In the Proceedings of the 11th international conference on Intelligent user interfaces, (Sydney, Australia, January 29 – February 1, 2006). ACM, New York, NY, 171–177.

Fisher, J. D., A. Nadler, and S. Whitcher-Alagna. 1982. "Recipient Reactions to Aid." *Psychological Bulletin* 91 (1):27–54.

Graesser, A. C., and N. K. Person. 1994. "Question Asking During Tutoring." *American Educational Research Journal* 31 (1):104–137.

Graesser, Arthur C., S. Lu, G. T. Jackson, H. H. Mitchell, M. Ventura, A. Olney, and M. M. Louwerse. 2004. "AutoTutor: A Tutor with Dialogue in Natural Language." *Behavior Research Methods* 36 (2):180–192.

Graesser, Arthur C., Katja Wiemer-Hastings, Peter Wiemer-Hastings, and Roger Kreuz. 1999. "AutoTutor: A Simulation of a Human Tutor." *Journal of Cognitive Systems Research* 1:35–51.

Harackiewicz, J. M., K. E. Barron, P. R. Pintrich, A. J. Elliot, and T. M. Thrash. 2002. "Revision of Achievement Goal Theory: Necessary and Illuminating." *Journal of Educational Psychology* 94 (3):638–645.

Harper, K. A., E. Etkina, and Y. Lin. 2003. "Encouraging and Analyzing Student Questions in a Large Physics Course: Meaningful Patterns for Instructors." *Journal of Research in Science Teaching* 40 (8):776–791.

Jensen, R., C. Tasoluk, C. A. San Mateo, M. J. Sims, H. Marshall, F. L. Orlando, and G. Green. 2007. "Integrating Intelligent Structured Training with a Virtual Dismounted Environment." In the Proceedings of the Interservice/Industry Training, Simulation, and Education Conference, (Orlando, FL). National Training and Simulation Association.

Johnson, B. G., F. Phillips, and L. G. Chase. 2009. "An Intelligent Tutoring System for the Accounting Cycle: Enhancing Textbook Homework with Artificial Intelligence." *Journal of Accounting Education*:30–39.

Karabenick, S. A., and J. R. Knapp. 1991. "Relationship of Academic Help Seeking to the Use of Learning Strategies and Other Instrumental Achievement Behavior in College Students." *Journal of Educational Psychology* 83 (2):221–30.

Kodaganallur, V., R. R. Weitz, and D. Rosenthal. 2006. "An Assessment of Constraint-Based Tutors: A Response to Mitrovic and Ohlsson's Critique of 'a Comparison of Model-Tracing and Constraint-Based Intelligent Tutoring Paradigms'." *International Journal of Artificial Intelligence in Education* 16 (3):291–321.

Koedinger, Kenneth R., and Vincent Aleven. 2007. "Exploring the Assistance Dilemma in Experiments with Cognitive Tutors." *Educational Psychology Review* 19 (3):239–264.

Lane, H. C. 2006. "Intelligent Tutoring Systems: Prospects for Guided Practice and Efficient Learning." In the Proceedings of the Science of Learning Workshop (Whitepaper), (Hampton, VA, August 1–3, 2006).

Lester, J. C., S. A. Converse, S. E. Kahler, S. T. Barlow, B. A. Stone, and R. S. Bhogal. 1997. "The Persona Effect: Affective Impact of Animated Pedagogical Agents." In the Proceedings of the SIGCHI conference on Human factors in computing systems, (Atlanta, GA, March 22–27, 1997). ACM, New York, NY, 359–366.

Marbach-Ad, G., and P. G. Sokolove. 2000. "Can Undergraduate Biology Students Learn to Ask Higher Level Questions?" *Journal of Research in Science Teaching* 37 (8):854–870.

Mercier, J., and C. Frederiksen. 2008. "The Structure of the Help-Seeking Process in Collaboratively Using a Computer Coach in Problem-Based Learning." *Computers & Education* 51 (1):17–33.

Moore, Michael G. 1989. "Three Types of Interaction." *The American Journal of Distance Education* 3 (2):1–6.

Nelson-Le Gall, S. 1981. "Help-Seeking: An Understudied Problem-Solving Skill in Children." *Developmental Review* 1 (3):224–246.

Newman, R. S. 1998. "Adaptive Help Seeking: A Role of Social Interaction in Self-Regulated Learning." In *Strategic Help Seeking: Implications for Learning and Teaching*, edited by S. A. Karabenick. Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Porayska-Pomsta, Kaśka, Manolis Mavrikis, and Helen Pain. 2008. "Diagnosing and Acting on Student Affect: The Tutor's Perspective." *User Modeling and User-Adapted Interaction* 18 (1–2):125–173.

Puustinen, M., O. Volckaert-Legrier, D. Coquin, and J. Bernicot. 2009. "An Analysis of Students' Spontaneous Computer-Mediated Help Seeking: A Step toward the Design of Ecologically Valid Supporting Tools." *Computers & Education* 53 (4):1040–1047.

Rickel, J., and W. L. Johnson. 1999. "Animated Agents for Procedural Training in Virtual Reality: Perception, Cognition, and Motor Control." *Applied Artificial Intelligence* 13 (4):343–382.

Roll, I., R. S. Baker, Vincent Aleven, B. M. McLaren, and Kenneth R. Koedinger. 2005. "Modeling Students' Metacognitive Errors in Two Intelligent Tutoring Systems." In the Proceedings of the 10th International Conference on User Modeling, (Edinburgh, Scotland, July 24–29, 2005). Springer, Berlin / Heidelberg, 379–388.

Ryan, A. M., and P. R. Pintrich. 1997. "'Should I Ask for Help?' the Role of Motivation and Attitudes in Adolescents' Help Seeking in Math Class." *Journal of Educational Psychology* 89 (2):329–341.

Sandoval, B. A., and F. Lee. 2006. "When Is Seeking Help Appropriate? How Norms Affect Help Seeking in Organizations." In *Help Seeking in Academic Settings: Goals, Groups, and Contexts*, edited by S. A. Karabenick and R. S. Newman. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Shah, H. 2006. "ALICE: An ACE in Digitaland." *tripleC - Cognition, Communication, Co-operation* 4 (2):284–292.

Soler, Eva Alcón. 2002. "Relationship between Teacher-Led Versus Learners' Interaction and the Development of Pragmatics in the EFL Classroom." *International Journal of Educational Research* 37 (3–4):359–377.

Sweller, J. 1988. "Cognitive Load During Problem Solving: Effects on Learning." *Cognitive Science* 12 (2):257–285.

VanLehn, Kurt. 1988. "Student Modeling." In *Foundations of Intelligent Tutoring Systems*, edited by M. C. Polson, J. J. Richardson and E. Soloway. Hillsdale, NJ: L. Erlbaum Associates.

VanLehn, Kurt, S. Siler, C. Murray, T. Yamauchi, and W. B. Baggett. 2003. "Why Do Only Some Events Cause Learning During Human Tutoring?" *Cognition and Instruction* 21 (3):209–249.

Varges, S., F. Weng, and H. Pon-Barry. 2008. "Interactive Question Answering and Constraint Relaxation in Spoken Dialogue Systems." *Natural Language Engineering* 15:9–30.

Walonoski, J. A., and N. T. Heffernan. 2006. "Detection and Analysis of Off-Task Gaming Behavior in Intelligent Tutoring Systems." In the Proceedings of the 8th International Conference on Intelligent Tutoring Systems, (Jhongli, Taiwan, June 26–30, 2006). Springer-Verlag, Berlin / Heidelberg, 382–391.

Wang, N., and W. L. Johnson. 2008. "The Politeness Effect in an Intelligent Foreign Language Tutoring System." In the Proceedings of the 9th international conference on Intelligent Tutoring Systems, (Montreal, Canada, June 23–27, 2008). Springer-Verlag, Berlin / Heidelberg, 270–280.

Webb, N. M., M. Ing, N. Kersting, and K. M. Nemer. 2006. "Help Seeking in Cooperative Learning Groups." In *Help Seeking in Academic Settings. Goals, Groups and Contexts*, edited by S. A. Karabenick and R. S. Newman. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

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