Modeling Tutoring Knowledge

Jacqueline Bourdeau, Monique Grandbastien

PRELIMINARY VERSION – PRELIMINARY VERSION -PRELIMINA

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Jacqueline Bourdeau[1] and Monique Grandbastien[2]
[1]Télé-université, University of Quebec in Montreal,
100, Sherbrooke W., Montreal (Quebec) H2X 3P2 CANADA
[2]LORIA, Université Henri Poincaré Nancy1
Campus scientifique, BP 239, 54506 Vandoeuvre Cedex, FRANCE
bourdeau@teluq.uqam.ca
monique.grandbastien@loria.fr

Abstract. This chapter introduces Part II on modeling tutoring knowledge in ITS research. Starting with its origin and with a characterization of tutoring, it proposes a general definition of tutoring, and a description of tutoring functions, variables, and interactions. The Interaction Hypothesis is presented and discussed, followed by the development of the tutorial component of ITSs, and their evaluation. New challenges are described, such as integrating the emotional states of the learner. Perspectives of opening the Tutoring Model and of equipping it with social intelligence are also presented.

1 Introduction

In the field of Artificial Intelligence in Education (AIED), the research on ITSs has attempted to develop, implement, and test systems that contain AIED principles and techniques. The "I" in ITS represents "intelligence" (AI techniques), the "T" is an abbreviation for "tutor," and the "S" signifies the application "software." In this chapter, the challenges of modeling tutoring knowledge are addressed, along with the problems that have arisen and have been dealt with, the solutions that have been tested, and the open questions that have been raised. This chapter begins by defining the term "tutoring", first, to distinguish it from education, instruction, and teaching, and, second, to place it in the context of ITS research. This chapter also provides insight into the following three main processes involved in building ITSs: modeling, developing, and evaluating the aspects and behavior of the tutoring system. This chapter concludes with a series of open questions.

2 What is Tutoring?

Since tutoring is a concept from the field of education, we start by looking at the origins and meaning of tutoring. We then analyze tutoring in the context of ITSs, as well as its functions and variables. We lastly attempt to understand better why tutoring is the foundation of ITS research.

2.1 Tutoring in education

Tutoring has always been a form of education and a means of instruction. It has two main properties: 1) the tutor/student ratio is 1/1-3(in most cases 1/1), so tutoring is often interpreted as individualized instruction since the attention of the tutor is totally focused on one student; 2) guidance or tutor control occurs, although this control may be shared with the student by means of guided discovery or cognitive apprenticeship (Collins, 2006). To understand tutoring better, two aspects of education need to be clarified. Whereas instruction focuses on the role of the instructor, learning focuses on the processes conducted by the learner, which may occur with or without formal instruction. Tutoring focuses on the personalization of the instruction-learning process through various types of interactions. Although instruction and learning are often considered two different processes, they can also be considered one entity defined by the interactions between the two: This is called "Instructional-Learning Event" in the OMNIBUS ontology (see Chapter 9). Tutoring is also seen as a locus of control, fluctuating between single or mixed initiatives. From this perspective, the Socratic dialogue is led by the tutor, who keeps questioning the learner until she becomes knowledgeable and aware of this process, i.e. learning. In terms of adaptation, tutoring plays a contrary role to teaching: A teacher requires the students to adapt to the class, whereas a tutor adapts to the student. Both tutoring and teaching are roles, which may overlap in real settings and be played by the same person.

2.2 Tutoring in ITSs

After extensive research, the ITS community has come to realize that tutoring with ITSs involves, in fact, not merely guidance from the tutor, but also interaction between the tutor and the learner, who work together as a duo (Graesser et al., 2001). This interaction may be a single or mixed initiative. Whereas teaching can happen without explicit interaction (and ultimately with no learning), such as is the case when lecturing, tutoring cannot. Interaction between the tutor and student, as well as ongoing and active adaptation on the part of the tutor, is a fundamental feature of tutoring. Consequently, the main challenge for the tutoring component of an ITS is to design interactions so as to obtain a precise adaptation and to shape the tutoring behavior by reasoning about virtually real-time data from the regular interactions between the learner and the system, for example, with machine learning techniques. While the work on student and agent models is continuing to evolve in ITS research design, the tutoring function is constantly being revisited and occupies a central position in ITSs and ITS research (Graesser & al., 2001; Heffernan, 2001; Lajoie et al, 2001; Virvou, 2001). The research on the Interaction Hypothesis is continuing to grow: At the ITS 2008 conference, VanLehn introduced the notion of the "Interaction Plateau," claiming that interactivity can only be taken to the level of "natural tutoring," beyond which learning effectiveness might decrease (VanLehn, 2008).

The original challenge of matching the success of good human tutors remains constant in ITS research. The research agenda is vast: The objectives are, first, to define and, as much as possible, to reproduce the tutoring functions and the tutoring variables; second, to find out what "causes" success; and, third, to determine how to measure success within and while interacting with an ITS.

2.3 Tutoring functions

The two main functions of instruction and, therefore, of tutoring are to foster and assess learning, both of which ITS research has mainly addressed separately and sometimes together, as in (VanLehn, 2007) and in Heffernan and Koedinger's ASSISTment system (see Chapter 21). The term "ASSISTment" was coined by Koedinger to combine "assistance" and "assessment." Although "assistance" implies that the control is with the learner, in the case of "ASSISTment," the definition is broadened to mean that the learner is helped through guided assistance or guided discovery. Tutorial dialogue design and management have been a focus for the team at the University of Memphis for a decade and are reported in Chapter 8.

When and how to assist or tutor learners is the fundamental dilemma of tutoring, as discussed in the papers entitled *To Tutor or Not to Tutor: That is the Question* (Razzaq & Heffernan, 2009b), and *Does Help Help*? (Beck & al., 2008).

Helping and tutoring the learner can be divided into two sub-functions: cognitive diagnosis, defined as the detection of the sources of errors, and the selection of tutoring or remediation strategies.

By considering the emerging capacity of ITSs to compute the learner's affective states (see Chapters 10 & 17), new challenges are being addressed by researchers, such as how to balance cognitive and motivational dimensions in tutorial strategies (Boyer & al., 2008). This latest development has added to the complexity of computing the learner's states (cognitive, meta-cognitive, and affective) and reasoning abilities in order to make optimal tutoring decisions.

2.4 Tutoring variables

An ITS researcher is confronted with a multitude of variables when designing a tutoring system: Who, What, How and Where does the tutoring happen? Each decision presents its own questions and challenges. Managing the interdependencies of a tutoring system is a challenge in itself.

The first question that an ITS researcher should ask is: Who is the learner? The first variable is the learner's characteristics: age, previous knowledge and skills, motivation, goals, culture, learning difficulties, etc. Knowing the learner is a necessary condition for adapted and adaptive tutoring. ITS research has long focused on how to induce the cognitive states of the learner. The emotional state of the learner is a new variable that has only recently been taken into consideration. Detecting emotions in real time and taking them into account in adapting the tutor is a broad field for investigation.

The second question that an ITS researcher should ask is: What is being tutored? The second variable is defined as the contents, subject matter, curriculum, or the "what-to-learn" in the OMNIBUS ontology (see Chapter 9). Classifications of this variable include the characteristics of the domain (math, science, language, attitude learning), the topics (concept or rule learning), the skills (problem solving, reading, writing), and the competencies.

The third question that an ITS researcher should ask is: How is the content to be tutored? This variable corresponds to tutoring strategies, such as scaffolding/fading, single or mixed initiative in dialogue, eliciting knowledge, errors or plans, diagnosing, planning, feedback/remediation, steps/hints, intervening/refraining, stimulated and support learning from errors, providing multiple visualizations, orchestrated collaborative learning, manipulation of variables, and selecting an assessment strategy. Most of the fundamental questions concern not only the adaptability of the system, but also the effectiveness of the tutoring, such as: "When are tutorial dialogues more effective than reading?" (VanLehn & al., 2007).

The last question that an ITS researcher should ask is: In what context is the tutoring taking place? This last variable can be interpreted in several ways: the physical context (i.e., classroom, workplace, home environment, distance learning, mobile learning, and web-based learning), the cultural context (see Chapter 23), the cognitive context, or the affective context. Whereas the first three categories of variables have been extensively used in existing ITSs, the fourth one is more recent. Indeed, the context has been implicitly limited to one learner in front of one computer. The limited knowledge of the context appears to be a major drawback in ITS development at this point.

2.5 Tutoring as a foundation for ITS

AIED was emerging as a field of study (Wenger, 1987) when Bloom (1984) published the results of his 10-year studies, and Cohen et al. (1982) published their meta-analysis on tutoring. Bloom's studies revealed a 2-sigma effect of tutoring over group instruction. Consequently, Bloom called for effective group instruction since the cost of tutoring was too high. However, AIED researchers saw promising possibilities for building effective systems that could foster and assess learning effectively and efficiently with tutoring, since using costly human tutors for each student was not an option, except in exceptional situations such as private tutoring or distance learning[1]. Developing appropriate and effective tutoring systems, thus, became the challenge of many AIED researchers. However, this focus soon became the subject of controversy due to its tutor-centered view. The ITS community has since been open to different perspectives (Vassileva & Wasson, 1996; Lajoie, 2000) and has evolved in such a way that tutoring has come to include many approaches to foster and assess learning. These approaches are presented in the following chapters.

3 Modeling Tutoring Knowledge

If the goal of an ITS is to be at least as effective as a good human tutor, and if being so requires that ITSs mimic human tutors, what should the tutoring model consist of in ITSs? Human tutors generally have a comprehensive knowledge of the curriculum, cognition and learning, and tutoring strategies. They have: a) facts about the student that they update regularly, b) perceptions of the student's personality and moods, and c) the ability to modify their tutoring strategies in order to optimize the learning experience with the student. The objective of this chapter is not to provide an in-depth analysis of past and present attempts to model tutoring in ITSs, but rather to highlight key issues.

Section 3 looks at four aspects of tutoring knowledge. First, it presents the different sources of tutoring knowledge and their role in modeling the tutor. Second, it characterizes tutoring. Third, it defines tutoring. Lastly, it briefly discusses the issues raised by the design of different tutorial interactions.

3.1 Sources of tutoring knowledge

In their paper entitled, *Modeling human teaching tactics and strategies for tutoring systems*, duBoulay & Lukin (2001) noticed "three principled methodologies for developing the teaching expertise in AIED systems, namely the observation of human teachers, the study of learning theories and the observation of real students interacting with online systems." These three procedures must still be considered today. As the challenge is to reach the success of good human teachers, it is worthwhile to observe their teaching behavior. However, it is important to note the differences between teaching in a classroom setting with a human teacher and tutoring with an ITS. First, tutoring 1/1-3 students is different from teaching a class of 30 or more students. Second, duBoulay & Luckin (2001) question "…whether tactics that are effectively applied by human teachers can be as effective when embodied in machine teachers." Third, Grandbastien (1999) mentions that: "Last, but not least, existing teaching expertise was mainly built without computers in the schools." Indeed, although computers have been used for learning purposes for several decades now, there is a lack a studies focusing on how tutoring guidance and decisions differ when they are to be implemented out of or within interactive environments. An attempt is being made to bridge this gap by keeping teachers in the design loop when building ITSs. The observation of novice tutors in schools was a primary source for designing AutoTutor, just as the observation of expert tutors is the main one for developing the Guru system (Chapter 10).

Several researchers in the field of ITSs have based their work directly on cognitive theories (see Chapter 11), or on collaborative and social learning theories (Greer et al., 1998). The main theories that

[1] In distance learning (e.g., Tele-University), the learning activities and contents of a course are designed by a professor to allow for independent study, and the dialogue with the student is conducted by a human tutor over the phone or by e-mail.

have been used as sources of tutoring knowledge are the following: Bloom's Mastery Learning, Anderson's Cognitive Theory – ACT-R- (Koedinger and Corbett, 2006), Vigotsky's Zone of Proximal Development (Luckin & duBoulay, 1999), and Gagne's instructional design theory (Pirolli & Greeno, 1988; Nkambou & al., 2003; Murray, 2003). Sources of theoretical knowledge on learning and instruction were reviewed in Greeno et al. (1996) and, more recently, in the collection of theories edited by Sawyer (2006).

Sources of practical teaching knowledge pose serious difficulties in terms of formalizing and modeling (Grandbastien, 1999; duBoulay & Luckin, 2001), since teaching practice is ill-defined and hard to systematize. Moreover, the idea of merging theoretical knowledge with practical knowledge into a united knowledge model remains an open problem. However, studies continue to be conducted in the areas of the observation and systemization of the behavior of tutors and teachers in ITS research. The structuring of a simple tutor dialogue was the basis for AutoTutor (Graesser & al, 2001), and the concept of map modeling has been proposed for building the Guru system (Chapter 18).

Another source of knowledge that may improve ITS behavior originates from the data collected from the learner's interactions with the system. The challenges for data mining and machine learning techniques in ITS research are well-documented in Part III and in Woolf's recent book (2009). Educational Data Mining (EDM) has recently evolved as an autonomous field of research. This field gives its own conferences, even if most researchers contribute to both ITS and EDM.

Making knowledge explicit from all sources contributes to the domain of AIED, just as it would for any domain, and contributes to the advancement of the learning sciences; it is also instrumental in building tutoring systems. Declarative knowledge, as in ontology, provides a better opportunity for criticism than procedural knowledge, and promotes discussions which can be consensus-building.

Given the heterogeneity of the various sources of knowledge, it is difficult to characterize and define tutoring.

3.2 Characterizing tutoring

In contrast to the tradition in ITS research, which is to define and describe ITSs through their structure and components, VanLehn (2006) proposed in his study to characterize ITSs through their behaviors. He considered two loops in a tutoring system: an outer loop at the task level and an inner loop at the step level. His claim was that only systems that have inner loops can be called ITSs, since they demonstrate the adaptive capability of the systems. This claim was criticized by both duBoulay (2006) and Lester (2006). duBoulay stated that this characterization "…applies only to a certain subclass of ITSs (…) whose intelligence is devoted to maximizing the chances [the student has of learning] how to solve a certain kind of multi-step problem in technical domains. (…) [T]he two loop structure can still be imposed on the behavior of the system, but the nature of what counts as a step and a task may differ." Lester supported duBoulay's statement by describing what he called "the KVL Tutoring Framework" He stated that VanLehn has "distilled more than three decades of research into a generic procedure defined by two nested loops that iterate over tasks and steps," and this framework "marks the arrival of AI in education as a mature field." However, he imagined that, in the future, one could question "the lack of ill-defined task domains and the dearth of fielded systems." He concluded by saying that this framework implicitly provides a research agenda and could serve as a roadmap for AIED researchers.

In an earlier article, Graesser, VanLehn et al. (2001) reflected on the complex nature of tutoring and proposed the Interaction Hypothesis. They conducted a detailed analysis of interactions in several developed ITSs. They described how these interactions were structured and expressed and how the student's expressions were predicted, interpreted and assessed. The tutoring strategy in Graesser's AutoTUTOR is based on structured dialogues in natural language with an "understanding" of the student's expression. The dialogue is guided by an agent that gives encouragement, approval, or other feedback. The interactive strategy in VanLehn's ANDES for problem solving in physics relies upon model tracing. It tracks the student's actions and adapts the dialogue accordingly. It should be noted that Graesser et al.'s (2001) conclusions drew upon dialogues in natural language and may not apply to systems that use speech recognition, such as LISTEN (Mostow & al., 2001), or sketch recognition (see Chapter 12).

Characterization of ITSs remains a constant concern, as illustrated above by VanLehn and Graesser's efforts. Its definition, therefore, continues to evolve, as presented in the next section.

3.3 Towards a definition of tutoring in ITSs

In 1999, John Self distinguished ITSs and ITS research; he characterized ITSs as systems that support learners:

ITSs are computer-based learning systems which attempt to adapt to the needs of learners and are therefore the only such systems which attempt to 'care' about learners in that sense. Also, ITS research is the only part of the general IT and education field which has as its scientific goal to make computationally precise and explicit forms of educational, psychological and social knowledge which are often left implicit.

The first part of the definition of tutoring highlights the adaptive nature of ITSs as being central. The last part of the definition stresses the need for ITS researchers to contribute to the learning sciences. If the notion of "caring" can be interpreted as an attentive and sensitive adaptation to the cognitive and emotive states of the learner, it is somehow equivalent to good "tutoring."

Both this perspective and that of the Interaction Hypothesis (Graesser & al., 2001) permit tutoring with ITSs to be defined as fostering and assessing learning through adaptive interaction between the student and the system. Other people (e.g., teachers, students, workers) can be in the loop, but they are external and unrecognized by the system, except in Computer Supported Collaborative Learning (CSCL) and in Social Learning.

3.4 The design of the tutorial interaction

As a consequence of this hypothesis, the key to the success (performance) of tutoring in ITSs is the design of the tutorial interaction. The design of ITSs must enable the designers to answer the question: Will the ITS enable dialogue, or not? Since dialogue is the most natural form of interaction, and, since it enables fine-tuned adaptation, dialogue in natural language has become central to many ITSs, despite the many challenges associated with it (Graesser & al., 2001).

An alternative to tutoring through dialogue is tutoring through actions by the use of a rich interface, such as in Andes (see Chapter 19). In this case, the following question arises: At what level is dialogue effective (VanLehn & al., 2006)? Putting agents or animated agents in charge of the tutoring is another alternative, as demonstrated by Johnson & al. (2000) and Chen and Wasson (2002).

In Discovery Learning Environments (DLE), tutoring is embedded in: 1) the simulation itself, which is a representation of a world or a phenomenon; 2) the allowed manipulation of variables by the learner; and 3) the feedback provided by the system. In a DLE, very little, if any, of the interaction between the tutor and the student occurs by means of a dialogue. Rather, the student and tutor communicate to one another via the student's actions (the manipulation of variables) and the feedback of the system (behavior or data). Most DLEs combine both dialogue and simulation.

3.5 Tutoring and collaborative learning

In 1988, Chan proposed tutoring one student first with a computer agent called "The computer as a learning companion," then with "Reciprocal Tutoring" and then with "Distributed learning companion systems" (Chan & Buskin, 1988; Chan, 1992; Chan & al, 1996). This line of research has further developed within ITS research under CSCL, which was presented in the "Special Issue on Computer Supported Collaborative Learning" of *IJAIED Journal* (1998), and has since been presented in all *ITS Proceedings*. It has evolved into an independent field, with a number of researchers working in both ITS and CSCL, for example, on ontologies for structuring group formation (Isotani & Mizoguchi, 2008) and intelligent agents to support collaborative learning (Wasson, 1998; Chen & Wasson, 2003). In CSCL environments, learning activities are often not seen as "tutored." However, several teams have worked on activities in scenarios or scripts so as to create a way of integrating guidance. In CSCL research, an attempt to build adaptive scripts and to use learners' data for this adaptation is seen as equivalent as seeking adaptability in ITS research (see Chapter 22).

3.6 Tutoring and adaptive web-based learning

Brusilovsky started the area of research on Adaptive Hypermedia systems (Brusilovsky, 1995) and edited the 2003 special issue of the *IJAIED Journal* on "Adaptive and Intelligent Web-Based Systems" (Brusilovsky & Peylo, 2003). These systems attempt to be more adaptive than other systems as they are able to build a model of the goals, preferences and knowledge of each individual student and use this model throughout the interaction with the student in order to adapt to his/her needs. They integrate individual tutoring by incorporating and performing some activities traditionally executed by a human teacher - such as coaching students or diagnosing their misconceptions. The tutoring decisions result in few dialogues between the tutor and the learner and the decisions are mainly based on changing the way the system displays the subject matter to the learner (presentation adaptation) and on the availability/advice of the links to be followed from the page presented (navigation adaptation). The model used in Adaptive Hypermedia systems provides most of the control to the learner. As did EDM and CSCL, Adaptive Hypermedia has developed as an autonomous field and holds biannual conferences. In 2007, Israel & Aiken proposed an integration of CSCL and Intelligent Web-based Systems, which seems promising.

4 Developing a Model of Tutoring Knowledge

Although the term "modeling" can be interpreted in different ways (Baker, 2001), this section defines "tutor modeling" as any form by which researchers try to conceptualize and to operationalize tutoring functions and variables. The first point considered is the location of the tutoring model in the conceptual architecture of an ITS. Next, a brief review of the current work and perspectives on the modeling of tutoring knowledge is examined. This section concludes by providing a perspective on the opening of a tutoring model.

4.1 A tutoring model in an ITS architecture

A key issue in tutor modeling depends on various perspectives and, as such, the following questions need to be considered: Where in the architecture is the tutoring model? Is it at the core or at the periphery of the system? Does the tutoring model have one distinct component? Are its tutoring functions distributed throughout in the system? Do the tutoring functions emerge strictly from the student's data? Are the tutoring functions integrated with the student model? Should the student model be one component of the tutoring model, as is the case in human tutoring? Does the system have a human teacher in the loop? If so, the tutoring functions are shared between the human teacher and the system. Thus, these two actors may or may not have a communication channel. Woolf's (2009) illustration of architectures that can combine classic components and emerging knowledge, while having two humans in the loop, highlights the complexity of the architectural design of ITSs (Fig. 1).

Figure 1: Components of machine learning techniques integrated into an intelligent tutor (Woolf, 2009, reprinted with permission)

The issue regarding architecture arises from the following questions and relates is to the paradigms used to create the IT'S: 1) Which cognitive architecture would be the most beneficial in the view of the designer? 2) What does she think are the appropriate sources for tutoring knowledge? 3) Should tutoring exist autonomously, or should it be incorporated in the student model or in the curriculum model? These fundamental choices govern the architectural design, the design of the tutoring functions and the consideration given to the tutoring variables. Tutoring is defined as having two main functions: fostering and assessing. It is modeled according to the cognitivist, contructivist paradigms used, the sub-functions (whom, what, where, when and how), and the design of tutoring interactions or dialogues. The instructional design decisions are modeled depending on one's theory, be it ACT-R, piagetian, vitgoskyan, or any other cognitive, learning or assessment theory. The challenges regarding the coordination of the interdependence between the components of emerging and specific knowledge also depend on one's fundamental choices, i.e., paradigms. In other words, modeling tutoring can be defined as a series of decisions made on how to foster and assess the learning of knowledge, skills and competencies. These choices emphasize either the cognitive, meta-cognitive, or emotive dimensions; the individual consciousness, the context, or the collaboration; or very complex issues, such as cognitive diagnosis.

4.2 Reclaiming tutoring knowledge

Most research teams in the field of ITSs often incorporate tutoring knowledge in the domain model or the student model, depending on where they believe it would be the most appropriate. Heffernan's dissertation title explicitly expresses the concern that some researchers have regarding the weakening role of the tutor in ITSs: "ITS have Forgotten the Tutor" (2001). As a result, researchers are once again acknowledging the key role that tutoring knowledge plays in making tutoring decisions. Grandbastien (1999) reclaimed practical teaching knowledge; Heffernan (2001) as well as Virvou (2001) modeled human instructors; Pirolli & Greeno (1988) and Murray (1999, 2003) had instructional design knowledge as being central to ITSs; Hayashi et al. (2009) claimed that theoretical tutoring knowledge is a foundation to decision-making regarding tutorial strategies and instructional design tasks. This debate has been a productive one and has allowed for diversity. However, it has also limited the sharing and reusing when authoring ITSs, as this debate has fostered 'idiosyncratic' implementations.

4. 3 Authoring the tutor

This section provides an overview of current work and perspectives in the authoring of tutoring functions in ITSs (for an overview on authoring systems, see Chapter 18). As the previous section discussed, the tutoring functions are neither uniformly represented, nor consistently distinct from other functions or components. Some or all tutoring functions may be pervasive or prevalent in their components or agents, such as the diagnosis in the student model or the dialogue in the communication component. One possible exception is Heffernan's tutoring function (2001), in which he intentionally built and demonstrated a distinct tutoring component with reasoning capabilities. In addition to the paradigmatic issue, two current orientations, providing authoring tools rather than complete systems and increasing the accessibility and affordability of authoring ITSs, are discussed in Chapter 18.

The issue of strong dependence of tutoring functions on the ITS architecture is also true of authoring systems or tools, as illustrated by Woolf (2009). The availability of authoring processes and tools is determined by whether or not a tutoring function is distinct, autonomous, or pervasive.

Where is research in this field heading? A decade ago, Murray (2001) suggested that ontologies would be instrumental in authoring ITSs. In 2000, Mizoguchi and Bourdeau (2000) anticipated that ontological engineering would serve this purpose and expressed their desire for an ontology that would respect the diversity of ITSs, while serving the field with tutoring strategies explicitly anchored in either theoretical or empirical knowledge. Will this be a reality in the next 10 years? Hayashi et al. (2009) paved the way in this direction, suggesting that the ITS community commits to ontologies that would allow for sharing and reuse, as well as making tutoring strategies explicit and capable of being examined and edited.

4. 4 Opening the tutoring model

Although some systems have been widely distributed, there are few products available for teachers and little enthusiasm from teachers to use them. One of the many reasons is that adaptation to the learning context is still weak compared to what a human actor can actually do. Grandbastien (1999) observed that teachers are willing to use products that enable them to be creative: Teachers need professional tools in the same way that craftsmen need theirs. In order to give human tutors these tools, the tutor model should be opened to them. However, the following questions would need to be addressed:

In what context could the tutor model be opened?

The opening could involve the preparation of the learning sequence (e.g., adding or replacing exercises), and of the behavior of the system during the learning sequence itself (e.g., weighing strategies in accordance with personal preferences), and the exploitation of post-session feedback.

For whom and for what purpose could the tutor model be opened?

Attempts to give more initiative to teachers to tailor ITSs to their needs are not new. For instance, in their paper entitled *Teachers implementing pedagogy through REDEEM*, Ainsworth et al. (1999) explained that REDEEM could be used as an authoring tool by teachers who had no previous experience, but it was still *authoring.* Current initiatives aim at providing flexible environments to meet the various needs expressed by educators: the PEPITE system (Delozanne & al., 2008), which includes a multi-criteria automatic assessor for high school algebra, and the ASSISTment Builder (Razzaq & al., 2009a; see Chapter 21). The PEPITE system provides the teacher a with a range of possibilities starting from building a complete set of assessment exercises to retrieving an exercise from an existing bank and using it as provided, or adapting the statement of the exercise by filling out forms. In addition to the raw answers, the teacher obtains an overall view of each student's competency in algebra, as well as the competencies of groups of students with similar student profiles. Once tailored to the user's needs, the environment may also be used independently by the learner to check her competencies and to access exercises adapted to her profile.

In the aforementioned specialized authoring tools, the tutor modeling aims to give more initiative to teachers. Moreover, opening the tutor model emphasizes the significance of opening the learner model, which has been investigated in much more depth (see Chapter 15). Consequently, further investigation is required to determine in which contexts and for which categories of learners the opening of the tutor model could improve learning.

5 Evaluating the Tutoring Model

The methodologies and tools used when studying and evaluating tutoring are of the utmost importance in ITS research. In her recent book, Woolf (2009) provides an extensive review of evaluation methods for ITSs. In addition, the *ITS '08 Best Paper Award* went to Beck. & al. (2008) for their paper comparing three methods of evaluating the efficacy of an ITS. When evaluation specializes in tutoring functionalities, the goal is to test the accuracy of the strategy, the effectiveness of the tools (error diagnosis, etc.), and/or the adaptability to individual situations. Making comparisons does not necessarily lead to the most meaningful results, and large *in situ* studies are often out of reach for small research teams. However, when available, the data gathered from large studies are of great significance in the field of ITSs and provide justification for their use in classrooms and other settings (Koedinger and Corbett, 2006).

Causality underlies many projects which aim at determining what might "cause" learning (VanLehn & al., 2003; VanLehn & al., 2007). However, it is difficult to prove or demonstrate a causal relationship; thus, hypotheses are presented as associations or correlations between events and situations. Current pitfalls in evaluating the tutoring function of ITSs are ill-defined hypotheses, biased and confounded variables, and weaknesses in the evaluation design and/or the interpretation of results (Woolf, 2009). In addition to the goal of testing the tutoring function, the goals of testing new techniques of visualization and detecting emotion need to be studied. As researchers are now able to compare methods of evaluating the same tutorial behaviors, exploration in this field of study is expanding (Zhang & al., 2008).

Advanced research teams (Cognitive Tutors, Constraint-based Tutors, DLE systems, AutoTUTOR systems) have constituted large corpora of data (from log files and other sources) together with analytical tools specific to their line of research. For example, the Pittsburgh Science of Learning Center has developed a data storage and analysis facility called Data shop, which has a series of analytical tools, such as the Error Report and the Learning Curve Generator (VanLehn, 2007). As a result, the potential for analysis has greatly improved and has developed the study of representations in ITSs. In addition, the concept of "steps" (the smallest possible correct entry that a student can make) has been revisited and become a key concept for cognitive tutors and their evolution.

Although Design-Based Research (DBR) is only in its early stages, it has much to offer to ITS research. This research paradigm has grown out the need to bring together design and *in situ* studies. It was built upon the general "design loop" with a series of sequences added to improve the design. The result is less control, but better R-D for educational innovations, with or without the use of technology (Barab, 2006). This approach might be more in line with system science and design science than methodologies originating from psychology or sociology.

In conclusion, even if the methodologies and tools for evaluating the tutoring functions in and with ITSs have developed extensively and even permitted progress in ITS research, such as the representation of tutor modeling, many questions remain unanswered. The following section describes some open questions that need further investigation.

6 Open Questions

Discoveries and development have been transferred from research labs to real educational settings during the last few decades. However, as ITSs are being implemented in schools, the interest, as was expressed at the workshop presented at the AIED conference in 2009, in scalability issues is growing among the community. Some of the scaling dimensions identified include: addressing curricula over long periods (e.g., one semester), learning product lines that interoperate with each other and span over a variety of learning platforms, and supporting large numbers of stakeholders (learners, teachers, institutions). Moreover new expectations continue to arise, and many challenging research questions require further investigation. In this section, we consider the following viewpoints: technology; affective, cognitive and contextual dimensions; and digital games.

6.1. Technology

The technological dimension of ITS tutoring continues to benefit from the progress made in Natural Language Processing (NLP software libraries), computer graphics (new interfaces), virtual agents and human-like avatars. Significantly improvement in natural language dialogue facilities has been and remains a crucial issue since dialogue is an essential component of human tutoring (Graesser & al., 2001). In addition to natural language, sketching is a common means for people to interact with each other in certain domains, and sketch modeling has become a new model for tutoring dialogues (see Chapter 12). Systems, such as Cog Sketch by Forbus (2009), also offer software that provides human-like visual and spatial representations.

New interfaces (e.g., complete immersion, haptic systems with force feedback) allow for the creation of new professional training environments which permit the authentic practice for real world skills that were not previously within the scope of computer-supported learning. Some interfaces include tutoring components, such as described in *VR for Risk Management* (Amokrane, et al., 2009a, 2009b).

Johnson, Rickel and Lester (2000) were the first to propose animated pedagogical agents. Recent techniques allow for the use of animated agents which have sophisticated and realistic facial expressions. In conjunction with virtual reality and virtual agents which act in the cultural environment of the learner, Johnson has developed Alelo's Tactical Language and Cultural Training Systems (TLCTS). Some of these systems, such as Tactical Iraqi ™ and Tactical French ™, are widely being used (Johnson & Valente, 2009). As a partial summary of their experiences, Lane & Johnson (2008) summarize principles that provide guidance in immersive and virtual learning environments. These systems have gone far beyond the aforementioned learning applications. It is due to the development of the videogame industry that the use of virtual reality and avatars is so widespread. The potential use of digital games in education is further discussed in Section 6.3. More research in the field of the use of virtual agents and human-like avatars in ITSs is of increasing interest.

6. 2. Affective, cognitive and contextual dimensions

Affect has been shown to have significant effects on learning. Recent advances in the tracking of facial features and other affect recognition techniques now make it possible to devise interactive tools that recognize and respond according to a student's affective states. Arroyo et al. (2009) used sensors to record physiological activity and compare them to students' self reports of emotions. Other achievements in detection and response to a student's emotions are described in Chapters 9 and 16. In addition, when ITSs are on the Internet, it is possible to obtain data from many real users, to use data mining techniques, and to use the results to determine and to record what the student is doing. It is also possible to improve the given product. Indeed, an in-depth understanding of a student's interests, intentions and emotions obtained from observing him/her while interacting on a website can improve the effectiveness of tutoring. Research in this area is significant and promoting new research will undoubtedly result in a new generation of systems that recognize the affective dimension of human behavior. However, (Conati & Mitrovic, 2009) point out that "we are still lacking from [sic] strong theories on how to use affect in pedagogical interactions and strong evidence that taking affect into account when interacting with student will actually improve learning." The situated cognition dimension is increasingly being implemented in virtual learning environments so as to promote learning activities in authentic social and physical contexts (Lane & Johnson, 2008).

As tutoring decisions may lead to a wide variety of activities for the learner, developing environments in which the built-in tutor and the classroom teacher complement each other, so as to optimize the support offered to the learner, is another possible means of implementing tutoring decisions. Integrating ITSs and the teacher results in opening the systems to the human tutor, and keeping the human tutor in the ITS design loop and the learning phase. It also means providing the human tutor with an overview of the learner's previous activities and results, as performed in the PEPITE system (Delozanne & al., 2008) and the ASSISTment system (Razzaq & al., 2009a) .

Although tutoring is mostly seen as a 1/1-3 process, from a social perspective, more collaborative environments are being proposed, thus making it possible to bridge tutoring systems and social web systems (Greenhow & al., 2009). Tutoring groups of online learners need new tutoring skills that can be recorded and implemented. ITSs should be instrumental in creating what McCalla called a "learning ecology" in his 2000 vision paper (McCalla, 2000).

With the semantic Web, tutoring knowledge is no longer limited to the tutoring module in ITSs. It is spreading. For instance, it can be embedded in the Learning Management System (LMS) and in Learning Objects Repositories (LOR) through tagging learning resources to fill metadata fields.

Lastly, investigating the empirical research in the neurosciences would be pertinent to researchers in the field of ITSs so they could better understand the overall learning process (cognitive, metacognitive, affective, social dimensions), e.g.: IRMf techniques. In fact, efforts to bridge education and neuroscience are underway (Varma & al, 2009) so as to bring a new light on the physical phenomenon of learning on the human brain by providing dynamic data and a systemic view of brain functions.

6.3 Digital games

Another dimension to consider when modeling tutoring knowledge is how learning occurs in contexts that radically differ from schooling, e.g., video games and support systems in the workplace. Since there are many specialized terms, concepts and techniques in this field, we will begin by presenting some definitions. First, since educational games existed long before videogames, it is important to understand the principles and lessons to be gained by educational games. Educational digital games are based on the attraction and motivation observed when children are engaged in games and learning activities in digital environments. For example, in order for a child to open a door for one of his/her favorite avatars, he/she has to perform a mental calculation to arrive at the answer. The more quickly he/she can determine the answer, the better his/her results. Following the educational digital games, came what was initially called "serious games." The term "serious game" is now used to name a variety of systems, most of which are simulation-based micro-worlds often containing complemented scoring systems. Alvarez & Rampnoux, (2007) from the European Center for Children's Products (University of Poitiers, France), have attempted to classify serious games into 5 main categories: Advergaming, Edutainment, Edumarket game, Diverted games and Simulation games. A serious game can be defined as a mental contest, played with a computer in accordance with specific rules that uses entertainment to further develop government or corporate training, education, health, public policy, and strategic communication objectives. Serious games are built with the principles and techniques originating from the video game industry and are inspired from the motivation that adults or groups have when playing these games. The idea is simple: Videogames which are designed for entertainment are being transformed into serious games. The hypothesis is that the people playing these games will have fun and, consequently, will learn through playing. However, the reality of the situation is complex and presents many unanswered questions. The main feature of entertainment videogames is their high motivation value. Consequently, the main question for serious game designers is how to foster learning without decreasing the intrinsic motivation to participate in the games. Moreno-Ger & al. (2009) provide an interesting overview of the synergies between digital games and e-learning. Johnson et al. explored the question: "Can AIED technologies complement and enhance serious games design techniques or does good serious games design render AIED techniques superfluous?" (Johnson & al., 2007). In his article *Deep learning Properties of Good Digital Games: How Far Can They Go*? Gee 2009) argues that learning occurs mainly because the design of such games is based on good learning principles and not due to gaming. Lane et al. support this in their papers (2008, 2009). However, they question the effectiveness of digital games as learning tools. Consequently, fundamental questions on this topic continue to emerge. As there is a growing interest in serious games, it is crucial to understand in which contexts, for which kinds of learners, and for which subjects digital games may be beneficial. Other questions include: How should assessments be integrated into the games? How should guidance (if any) be incorporated into the games? What is the nature of motivation in games? How does playing the games translate into learning for the student?

Tutoring strategies should include additional data about the learner (*e.g.,* modeling and tracking his/her activity over a longer period of time), as noted by Johnson & al. (2007). Another question to take into consideration is: Would it be better to alternate gaming and other activities, or would it be better to introduce new kinds of tutoring rules within a digital game architecture as a solution?

Besides the specific dimensions discussed above, more general open questions continue to be posed in this field: What has been learned from new settings involved in human instruction and integrated learning that could improve tutoring systems? Can they develop the ability to tutor? How can tutor modeling help researchers to understand more about human instruction? Should the tutor demonstrate emotions and a sense of consciousness? Can the fields of neuroscience and brain science inspire researchers in their future studies of ITSs?

7 Conclusion

In 2010, ITS research is developing with respect to the design of tutoring functions in planning, dialogue, and tutorial interaction design. Recent progress has been obtained with the design of systems based on machine-learning techniques that enable reasoning on student data. Among the challenges that remain are: a) integration as a means to obtain adaptability and effectiveness in tutoring; b) using real-time and other elements of context; c) improving accessibility and affordability; and, c) evaluating methodologies and tools to assess the many dimensions of tutoring in and with ITSs.

After a generation of research in cognitive-oriented ITSs, the use of emotions in ITSs is now being studied so as to have a deeper understanding of the student's cognitive-emotive state so that the tutor can better adapt to her state. With the advances in brain research in relation to social intelligence, are we going to see more effort to include this dimension in ITS research? Although the social Web has allowed for multiple (both teaching and non-teaching) activities based on social interactions, we have not yet seen research that focuses on the social dimension of learning with the same depth as the cognitive and emotive dimensions of learning. Integrating the cognitive and emotive aspects in ITSs is already proving to be quite a challenge. Research in the field of IT'S could prove to be all the more challenging if social intelligence were added to the equation. If the basis of ITS research pertains to models (Baker, 2001), and if "social intelligence is the new science of human relationships" (Goleman, 1996), then the field of ITS needs computational models of social intelligence, either as part of the student model, the tutoring model, or the interaction model.

In conclusion, our goal is to achieve a tutoring intelligence that gives rise to and evaluates learning, provides complete, in-depth support and is able to provide a service that is at least as good as that of an excellent human tutor.

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