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A Model of Affect and Learning for Intelligent Tutors

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Abstract: A model of affect and learning for intelligent tutoring systems is proposed. The model considers both how a student feels and what a student knows, and then customizes how instruction is presented and how learning and performance are reinforced. The model was designed based on teachers' expertise, which was obtained through interviews and interaction with an educational game on number factorization learning. The core of the model is a dynamic decision network, which generates tutorial actions balancing affect and knowledge. The student's affect representation relies on a Bayesian network and theoretical models of emotion and personality. A controlled user study to evaluate the impact of the model on learning was performed. Current results are encouraging since they show significant improvement in learning when the model of affect and learning is incorporated.

Keywords: affective intelligent tutor, teachers' expertise, user's study
Categories: J.7, K.3.1, L.2.2

1 Introduction

In recent years, artificial intelligence has made significant contributions to education and training fields; it enables building systems that can adapt to needs, expectations and preferences of students. Intelligent tutoring systems (ITS) are a very successful application of artificial intelligence [D'Mello and Graesser 2012]. An ITS aims to simulate the teaching patterns of human tutors, by keeping track of the particular state of each student, typically the knowledge state. An ITS is based on knowledge about the student (student model), knowledge about teaching (tutor module), and knowledge about specific domains (expert module), and it includes an interface module that presents the instruction in a suitable way.

Research has revealed the growing demand for considering emotions in ITS since they are very important for motivation and consequently for learning, and effective human tutors intuit what is happening with their students on a continuous basis [González-Sánchez et al. 2014, Sabourin and Lester 2014, Porayska-Pomsta et al. 2013, Piaget 2005, Vygotsky 1962]. This is a new frontier for artificial intelligence researchers.

There has been extensive work on modeling student emotions in ITS [Paquette et al. 2014, Arroyo et al. 2011, D'Mello and Graesser 2010, Conati and Maclaren 2009]; and psychological models relating affect and learning have emerged [Immordino-Yang and Damasio 2007]. However, there have been only few attempts to integrate information on student affect in the tutorial decisions [Frasson, Brosseau and Tran 2014, du Boulay 2013, Cooper, Arroyo and Woolf 2011].

Most of the research on recognizing and responding to emotions has been interested in detecting affective state. For example, Conati and Maclaren [Conati and Maclaren 2009] propose a probabilistic model of student affect; they propose detecting emotions from users' cognitive appraisal of current situation and sensors. A study where participants were asked to distinguish between affective states such as happy, tired, proud, bored, nervous, angry, and frustrated is presented in [Balaam et al. 2010]. A study on automatic detection of student affect is presented in [Paquette et al. 2014]; in this study students use simulation and support tools to engage in inquiry; they propose using a combination of data mining and ground-truth labels that were obtained from field observations of affect. An in-depth analysis of how learning interacts with affect and engagement in game-based learning is presented in [Sabourin and Lester 2014].

Despite the great progress achieved in modeling affect, there is much work to be done such as knowing which emotions are relevant for learning, and the level at which they are relevant depending on particular contexts, age, and so on. And perhaps, the most important thing is to know how the computer should react to user's emotions. In an educational setting, we need to know which emotions should be shown to the students to try to motivate and help them to learn according to particular tutorial scenarios. Additionally, it is very important to know which pedagogical actions (an example, an explanation, an exercise, or a test) are going to foster a good affective state considering the particular student, and those should also be pedagogically adequate.

In order to try to contribute to the understanding of the relationship between affect and learning, we focus on the actions and reactions that an intelligent system should have to the emotions of students. We conducted a study where we interviewed teachers and asked them what they do according to perceived, or maybe expressed, students' emotions. With the gathered knowledge we composed a model that relates affective states with tutorial actions. On the other hand, as an imperative component of the model, we use contextual information and personality traits to detect emotions. One advantage of the proposed methodology is that students do not have to use special equipment to interact with the systems. When students are required to use any equipment other than the computer, they can feel observed. This may lead to inauthentic behavior, and errors in the recognized state can occur.

The research described in this paper proposes a Model of Affect and Learning integrated into the decisions of an ITS. We have incorporated emotional and personality models as well as teachers' expertise. The model detects the affective state as proposed by the OCC Model [Ortony, Clore and Collins 1988] and it responds according to teachers' expertise. The model can be integrated to any ITS or educational computer program to add affect capabilities.

In this paper we describe the construction and evaluation of the Model of Affect and Learning. Section 2 describes the model. Section 3 describes the survey to gather teachers' expertise. Section 4 presents the student's affect model. Section 5 presents the affective tutor model. Section 6 presents the results of evaluation surveys. Finally, Section 7 discusses conclusions and future work.

2 Design of the Model of Affect and Learning

To achieve an affective behavior, that is to say, a tutor reacting to student emotions in a pedagogically appropriate time, we are proposing a model with three components: i) a student's affect model, ii) a tutor model, and iii) affective actions. In this section, we describe the model as a whole and the affective actions; while Section 4 describes the student's affect model and Section 5 describes the affective tutor.

An ITS aims to imitate how human tutors instruct. Traditionally, an ITS decides what and how to teach based on a representation of the student's knowledge. Misconceptions, errors, and trials may be part of this representation as well. These representations are focused on what students know and what students do not know. However, there is evidence that experienced human tutors cope with the affective state of students to motivate them and improve their learning process [Sabourin and Lester 2014]. Thus, if we can analyze this human ability and integrate it into an intelligent tutoring system, it will generate better results in motivation and learning.

In order to model and incorporate affect into an ITS, we need a way to know the student's affect. The student representation has to be augmented with that affective knowledge. Then, we need to model an affective tutor which makes decisions not just on pedagogical strategies but on what the student is feeling: his affective state. Thus, the student can be provided with a tutorial action which fulfills knowledge requirements and at the same time is appropriate to his affective state. The Model of Affect and Learning consists of three components: the student's affect model, the affective tutor, and the affective actions; see [Figure 1].

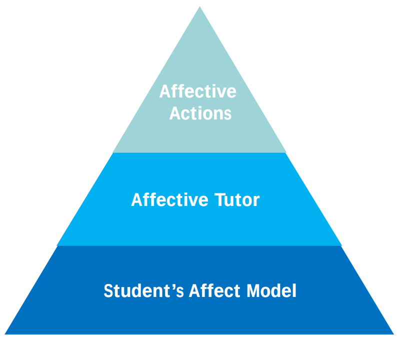

Figure 1: Model of Affect and Learning

The first component of the model is the student's affect model. The student's affect can be detected from different types of data, such as cameras, biosensors, contextual information, or even self-reports. In our case, we use contextual information such as tutorial situation and student's goals. The student's affect model is based on the OCC Model [Ortony, Clore and Collins 1988] and on the five-factor model of personality [Costa and McCrae 1992].

The OCC Model defines emotional state as the outcome of the cognitive appraisal of the current situation with respect to one's goals, principles and preferences. Thus, emotions represent a positive or negative reaction, with respect to the consequences of events, actions of agents, and aspects of objects [Ortony, Clore and Collins 1988]. The elicited emotion also depends on the relevance of the event, agent, or object to the individual. The OCC Model sets up parameters that represent the intensity of emotion. The basics of the OCC Model are shown in [Figure 2].

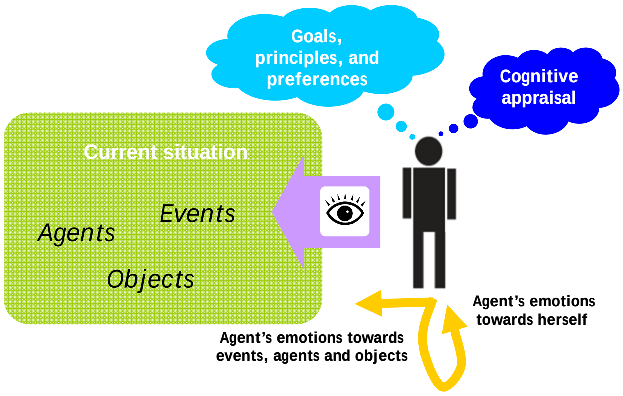

Figure 2: Fundamentals of the OCC Model

In a tutorial session there are events pertinent to learning, such as an explanation given by the tutor (tutor's event) or completion of an exercise (student's event). These events have an effect on the student and can elicit affective states such as joy and distress.

In the tutorial situation, there are two relevant agents: the student and the tutor. Both of these agents are active and the result of their actions provokes emotions in the students. For example, the student might feel pride or shame as regards to a particular action he performed; or the student might feel admiration or reproach as regards to an action the tutor performed. Results are attributable to the agent who carried out the action and, consequently the student's emotions are focused on that agent, i.e., the student feels pride or shame toward himself, or he feels admiration or reproach toward the tutor.

The OCC Model proposes 22 emotions classified according to their causes. From these emotions, our student's affect model takes six emotions: *joy*, *distress*, *pride*, *shame*, *admiration*, and *reproach*. The *joy* and *distress* emotions are reactions of the individual to an event in the tutorial session. The *pride* and *shame* emotions emerge as a consequence of the student's action. The *admiration* and *reproach* emotions emerge as a consequence of a tutor's action.

Goals are crucial for the affective state, as stated by the OCC Model. To understand the student's affect, goals cannot be explicitly asked to the student during interaction because, in order for the student to provide a reliable answer, he would need to have a clear understanding of the question and to be introspective; as a consequence, errors can occur. Therefore, the goals in our model are inferred from indirect sources of evidence: personality traits and student's knowledge. We based the personality traits on the Five-Factor Model [Costa and McCrae 1992]. This model considers five dimensions of personality: *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*. The Five-Factor Model describes each of these dimensions of personality and their characteristics of behavior. Our model includes only two dimensions: conscientiousness and neuroticism. We chose these two dimensions because they are the ones for which a stronger relationship with learning has been identified [Heinström 2010]. A relationship between openness and learning has been reported, but it has not been proven [Heinström 2010].

The second component of the Model of Affect and Learning is the affective tutor. The affective tutor integrates knowledge to reason with the affective student state and to produce an affective action. In this work, this knowledge is based on the expertise of a group of teachers. The teachers' survey is described below, see [Section 3]. The affective tutor produces an affective action, which helps the pedagogical tutor model to decide on which next on pedagogical action. Also, the affective action helps the interface module to decide on the physical realization of the pedagogical action. The affective action will be used in a way determined by the specific ITS and, particularly, by its tutor module and its interface module; that is to say, the domain of the ITS and the technology used in user interface. The integration of the Model of Affect and Learning with an ITS architecture is shown in [Figure 3].

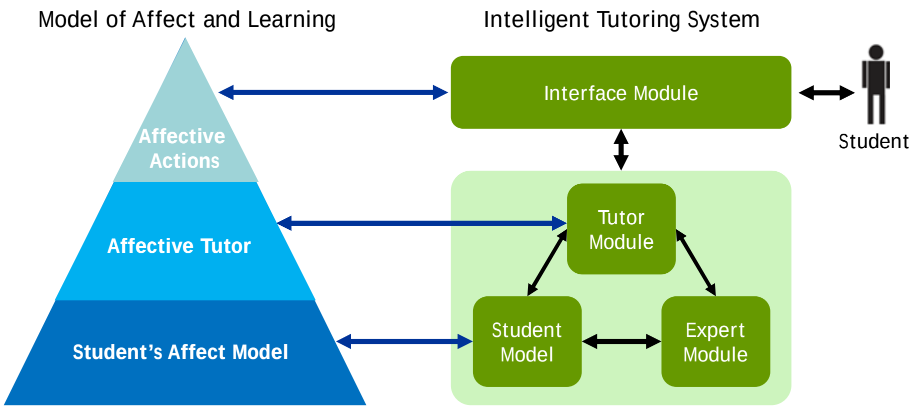

Figure 3: Integration of the Model of Affect and Learning with the architecture of an ITS

Affective actions are the third component of the Model of Affect and Learning. We identified three kinds of affective action: encouraging, enthusiastic and energetic. Encouraging and enthusiastic actions apply when the affective state is good, and motivation is great; the next pedagogical action of the tutor can use the same pedagogical strategy used at that moment, because the instruction is working. An energetic affective action applies when the affective state of the student is not good; the next pedagogical action has to attract his attention.

The affective action represents the basic movements of a human tutor. The affective action consists of two sub-actions: the pedagogical sub-action and the interface sub-action. The pedagogical sub-action gives information to the tutor module for the next pedagogical action. The pedagogical sub-action indicates whether the pedagogical action must stay within the same topic or change the topic, change the media, change the pace to faster or slower; but the pedagogical action (explain, exercise, example) and the exact pedagogical content must be established by the tutor module.

The interface sub-action gives useful information to the interface module for the physical realization of the tutorial action. An enthusiastic sub-action applies when the student is doing well. An encouraging sub-action applies when the motivation decreased because of an error, for example. An energetic sub-action applies when the student is not paying attention. However, the user interface technology decides what will be delivered to the student. For example, in the case of animated pedagogical agents, the tutorial action will be delivered with a facial expression and a voice tone, and in the case of text interfaces, the tutorial action will be delivered with words or colors. The structure of the affective actions is presented in [Figure 4].

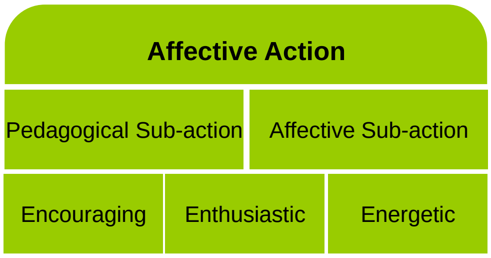

Figure 4: Affective Action structure

In the next section, we describe how we built the Model of Affect and Learning. We describe a survey to gather knowledge about teachers' expertise.

3 Getting Teachers' Expertise

In this section, we present the process of construction and implementation of the Model of Affect and Learning. Our domain test-bed is the Prime Climb educational game [Muir and Conati 2012]. The goal of Prime Climb is to help grade 6 and 7 students learn numbers factorization. Two players have to climb mountains in a collaborative way. Each mountain is composed of hexagons labeled with numbers. Players have to move to a number that does not have common factors with their partner's number. If they climb to a number having a common factor with their partner's number, they will fall off the mountain and will have to start climbing again. To give adequate instruction, Prime Climb relies on a Bayesian pedagogical student model [Muir and Conati 2012]. A pedagogical student model assesses the evolution of the student's factorization knowledge during interaction with the game. An animated pedagogical agent implemented through the Merlin Character of Microsoft Agent

[Microsoft 2010] uses the pedagogical student model to deliver textual hints. It should be noted that this pedagogical agent uses almost none of the animations available in Microsoft Agent. In [Figure 5] Merlin is giving instruction.

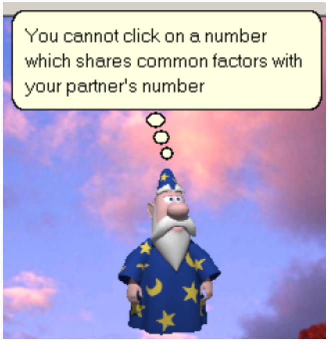

Figure 5: Merlin pedagogical agent giving a hint

Cristina Conati and her team developed Prime Climb [Muir and Conati 2012, Conati and Maclaren 2009]. They also developed an affective student model described in [Conati and Maclaren 2009], but we did not use this affective Prime Climb. Therefore, to test our work in Prime Climb, we integrated to it the three components of the Model of Affect and Learning: the student's affect model, the affective tutor, and the affective actions. The survey described a few lines below was carried out using the original Prime Climb and a version which includes our model.

3.1 Description of the Survey

Our work is based on an extensive survey with 20 skilled teachers. There are very few studies reported in literature with as many teachers participating [Sarrazfadeh et al. 2014, du Boulay 2011]. The survey aimed to support our assumptions and refine the model. We wanted to know which actions teachers take according to the affective and pedagogical student state. Also, we wanted to know why they select those actions. The teacher sample included 20 math teachers with an average of 17 years of teaching experience (from high school to post-graduate). These teachers are trained in several teaching methodologies. The survey asked teachers to watch a student interacting with the original Prime Climb. They were then asked to add in what affective and pedagogical actions they would take. We also asked them to explain their reasoning on why particular actions would help students to learn. Essentially, we were collecting expert opinions on a standard example: the video of the student interacting with Prime Climb.

The survey protocol was:

1. We explained the purpose of the study, main motivations, and hypotheses. We described the Model of Affect and Learning and the OCC Model briefly.
2. Teachers interacted with Prime Climb to become familiar with the educational game and how it works.

3. We showed the Microsoft agent animations and asked teachers which ones are suitable to provide affective tutorial feedback as affective action in Prime Climb.
4. We showed a video of a student playing Prime Climb and asked teachers to decide on specific affective and pedagogical actions for each situation.
5. We asked teachers three general questions about the relationship between affect and learning.

In sum, we explained teachers the context of the survey. We explained what affective action is in this work, and how we use Merlin's animations as affective actions to promote a positive affective state. We also explained that a tutorial action to be delivered to students is composed of an affective action and a pedagogical action. Then, the teachers interacted with Prime Climb as much time as they wanted to become familiar with the environment and to see different situations that could take place in a student interaction. Each teacher took an average of 90 minutes to complete the survey.

3.2 Merlin's Animations as Affective Actions

We showed the teachers the Merlin Microsoft Agent animations. We asked them which ones they considered suitable for affective tutorial feedback in Prime Climb. Merlin supports over 70 animations; examples are listed in [Table 1].

Animation	**Description**
Decline	Raises hands and shakes head
DontRecognize	Holds hand to ear
Process	Stirs caldron
Read	Opens book, reads and looks up
Search	Looks into crystal ball
Suggest	Displays light bulb
Sad	Sad expression
Think	Looks up with hand on chin
Wave	Waves

Table 1: Examples of Merlin' animations

We wanted teachers to be able to see the full range of Merlin's animations so they could select the animations they wanted to use in the next phase, but if they wanted they could have the complete set of animations available. Two teachers wanted all the animations available; they said they do so because they could not anticipate what they would be facing.

Teachers chose animations that they deemed to be appropriate to convey affective elements using a user interface. In [Figure 6] we show a screenshot of the interface; teachers could select any animation they wanted to be performed by the animated agent, as many times as needed.

Some animations consist of an animation loop, for example, "read" and "continue reading"; therefore, we had 58 animations to evaluate. As a result of this phase, we obtained the following: 17 animations were selected more than 5 times, 46 at least twice, 53 animations were selected at least once. Only 5 animations were not selected at all. We present the animations selected more than 5 times in [Table 2].

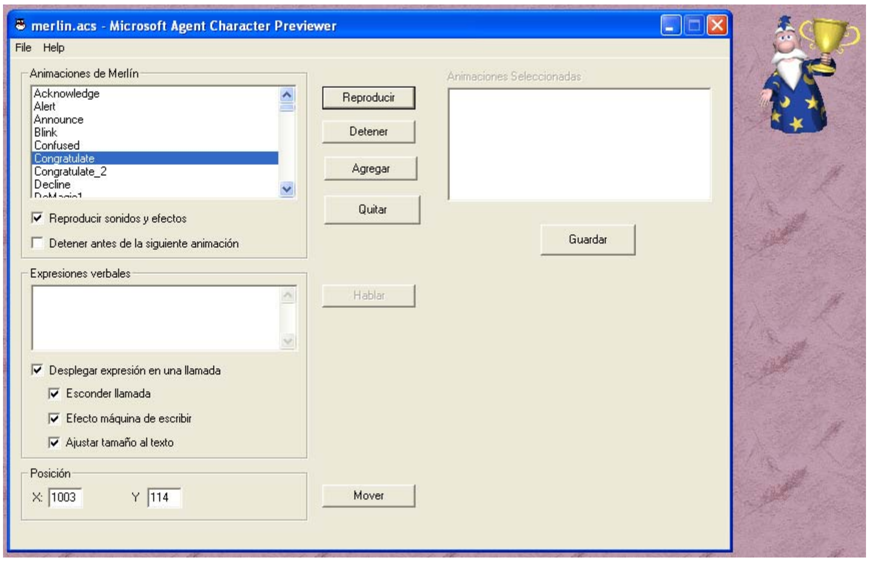

Figure 6: Screenshot of the interface to play animations of the Microsoft Agent (Mostly in Spanish). Merlin is playing the "Congratulate" animation

These results indicate that Merlin is a character with suitable expressivity to show tutorial actions and it can be used in an educational environment, since over 90% of its animations were judged suitable to convey affect in the teachers' opinion.

3.3 Student-Prime Climb Interaction

In order to solicit the teachers' opinion, they watched a video of the interaction of one student with Prime Climb. All teachers watched the same video. During this five-minute video, the student climbed three mountains (levels) and presented a variety of tutorial situations based on a mix of student's correct and incorrect behaviors. Although it would have been more principled to show the teachers interactions of several different students with Prime Climb, it was not possible due to constraints on teachers' availability. The interface of the program for the teachers' survey is shown in [Figure 7]; it consists of the following parts, identified with red circles: 1) the main panel is the video player; teachers could stop and replay the video as many times as they wished, 2) text boxes to type in information about the teachers, such as age, years of teaching, educational levels they teach, and so on, 3) combo boxes to identify the student's move, 4) sliders to rate the affective state of the student, 5) combo box to select the pedagogical action and text box to explain why it was selected, 6) combo box to select the affective action and text box to explain why it was selected, 7) text box to type in any comment teachers wanted to make, 8) button to save the record, and 9) button to exit the program.

Animation	Number of Times it was Selected
Confused	9
Congratulate_2	9
GetAttention	8
Hide	8
Read	8
Decline	7
Suggest	7
Announce	6
Congratulate	6
MoveDown	6
MoveLeft	6
MoveRight	6
MoveUp	6
Pleased	6
Process	6
Search	6
Show	6

Table 2: Examples of Merlin Microsoft Agent animations

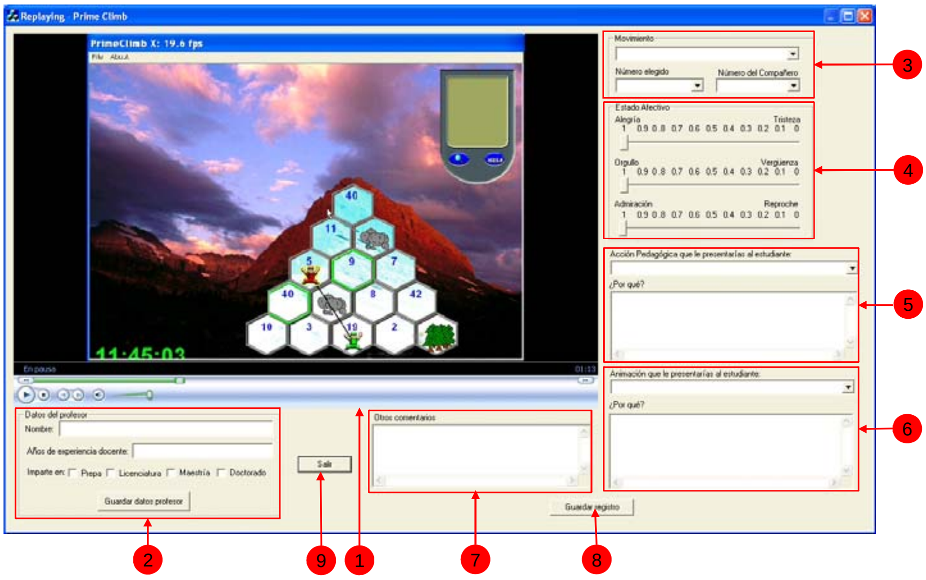

Figure 7: Interface of the program for the teachers' survey (in Spanish)

Teachers rated the student's affective and knowledge state after each student's move. These ratings were based on our model and on the OCC Model which had been explained to the teachers. The teachers established the pedagogical and affective components of the tutorial action that they considered adequate at that particular point. Teachers also gave us information on why they thought a selected action improved the student's affect and knowledge. An example of a teacher's report is presented in Table 3.

Parameter	**Value Assigned by the Teacher**	
Affective state:	Pride/Shame	75/25
	Admiration/Reproach	70/30
	Joy/Distress	73/27
Knowledge state:	Student knows the numbers factorization	
Pedagogical action:	Right, these numbers do not share factors	
Affective action:	Congratulate_2	
Pedagogical action explanation:	Student made a correct click	
Affective action explanation:	Student is having success	
Comments:	I try to motivate the student	

Table 3: Example of a teacher's report

This phase of the study was critical because it provided information on how teachers choose their actions, considering the affective and knowledge states of the students. This is knowledge we want to incorporate into the Model of Affect and Learning. Our main premise in this study is that teachers selected actions they believed would improve the students' affective state and knowledge. In this phase, teachers selected animations based on the affective and knowledge student state. In Table 4, we present the averages of affective states for each animation; these numbers help us set the utilities of affective actions on the affective student state in the decision network described below in [Section 5].

Affective Action	**Joy/Distress**		**Pride/Shame**		**Admiration/Reproach**	
Acknowledge	81.7	18.3	68.7	31.3	64.7	35.3
Announce	79.3	20.7	78.0	22.0	63.5	36.5
Congratulate	90.6	9.4	89.2	10.8	78.6	21.4
Congratulate_2	79.3	20.7	77.4	22.6	73.1	26.9
DoMagic1	85.0	15.0	78.0	22.0	71.5	28.5
DoMagic2	76.5	23.5	77.0	23.0	65.0	35.0
Greet	66.6	33.4	63.8	36.2	60.4	39.6
Hide	89.3	10.7	92.3	7.7	93.0	7.0
Pleased	71.3	28.7	63.8	36.2	59.4	40.6
Alert	23.7	76.3	44.0	56.0	40.3	59.7
Confused	42.2	57.8	53.0	47.0	55.0	45.0
Explain	59.0	41.0	34.0	66.0	23.5	76.5
GetAttention	38.7	61.3	47.7	52.3	48.0	52.0
Surprised	46.0	54.0	43.5	56.5	34.5	65.5

Table 4: Affective state averages for animations selected by teachers

Based on the teachers' responses, we selected 14 of the 58 animations as most potentially helpful as affective components of Merlin's interventions. The 14 selected actions are listed in Table 5. Seven of these animations were among the most selected by teachers in the previous phase.

Affective Action	**Animation Description**
A1-Acknowledge	Nods head
A2-Announce	Raises trumpet and plays
A3-Congratulate	Displays trophy
A4-Congratulate2	Applauds
A5-DoMagic1	Raises magic wand
A6-DoMagic2	Lowers wand, clouds appear
A7-Greet	Bows
A8-Hide	Disappears under cap
A9-Pleased	Smiles and holds hands
A10-Alert	Straightens and raises eyebrows
A11-Confused	Scratches head
A12-Explain	Extends arms to side
A13-GetAttention	Leans forward and knocks
A14-Surprised	Looks surprised

Table 5: Merlin's animations preferred by the teachers as affective actions

The teachers' reports were useful to describe the impact of affective and pedagogical actions on knowledge and affect, given the current student's state and outcome of student's action, namely the probabilities in the dynamic decision network to calculate the expected utility of actions. The dynamic decision network is described in [Section 5]. For example, when a student makes a successful move but seemed not to know the numbers factorization, teachers often selected the verbal hint "You're right again! But do you know why? Here's an example" (The example is an explanation of the factorization of the relevant numbers).

3.4 General Questions

We also wanted to know about the relationship between affect and teaching. We asked teachers the following three questions to get this additional information:

1. Do you take into account the students' current knowledge and affective state when you are teaching? Why?
2. Which is more important for you, knowledge or affect? Why?
3. As a teacher, can you classify your own teaching actions into categories?

Answers to Questions 1 and 2 are presented in [Table 6].

The third question asked teachers to classify their actions into categories. Answers here were general and open; therefore it was difficult to obtain a classification of teachers' answers. However, all the participating teachers stated that the aim of their actions is to motivate students, and the ultimate goal is to achieve student learning. Some of the categories mentioned are found in [Table 7].

Question	Answers	
1	Teachers who take into account only the students' knowledge	2/20 (10%)
	Teachers who take into account only the students' affect	1/20 (5%)
	Teachers who take into account both the students' knowledge and affect	17/20 (85%)
2	Teachers who think the students' knowledge is more important	6/20 (30%)
	Teachers who think the students' affect is more important	4/20 (20%)
	Teachers who think both states are equally important	10/20 (50%)

Table 6: Teachers' answers to questions 1 and 2. Do you take into account the student's current knowledge and affective state when teaching? And, which is more important for you, knowledge or affect?

Categories
Positive feedback
Negative feedback
Reward
Reprimand
Motivation
Get attention
Relaxing
Harder exercises

Table 7: Teachers answers to "Can you classify your actions into categories?"

4 Student's Affect Model

One of the first steps for having affective behavior in an ITS, is to understand the affect of the student. Our student's affect model is based on the OCC Model [Ortony, Clore and Collins 1988], on The Five-Factor Model of Personality [Heinström 2010; Costa and McCrae 1992], and on an affective student model previously defined in [Conati and Maclaren 2009].

The student's affect model is represented by a dynamic Bayesian network (DBN) that probabilistically relates student personality, goals, and interaction events with the student's affective states based on the theory defined by The OCC Model. The affective state is not static, but it changes over time as a result of the changing environment and the particular interpretation of the situation in each individual. The dynamic Bayesian network models the active nature of the affective state and how one state influences the next state. The network includes two time slices at any given time. A slice is added and a slice is discarded after each student's action. The DBN for the affective student model is shown in [Figure 8]. This is a high-level representation, since each node in the network is actually a number of nodes in the student's affect model. The detailed DBN is shown in [Figure 9], and a detailed description of the student's affect model can be found in [Hernández, Sucar and Arroyo 2012]. The dependency relationships in the Bayesian network have been established based on the literature [Ortony, Clore and Collins 1988, Costa and McCrae 1992, Heinström 2010].

As seen in [Figure 8], at time t_n the affective state is inferred by its relationship with reached goals, as stated by the OCC Model. Reached goals are inferred by means of tutorial situation and student goals (the student's cognitive appraisal). Goals are inferred by means of personality traits and the knowledge state of the student. The evidence for the *Knowledge State* node comes from the pedagogical student model. At the next time t_{n+1}, the overall student state is influenced by the student state at time t_n. The *Knowledge State*, *Goals* and *Affective State* nodes at t_{n+1} are influenced by *Knowledge State*, *Goals*, and *Affective State* nodes at t_n, respectively.

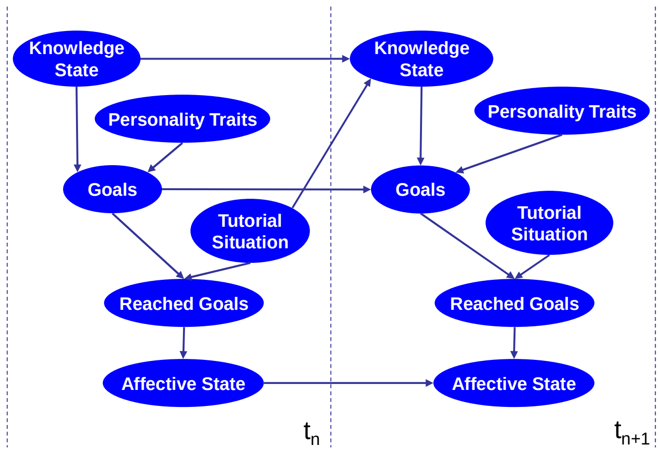

Figure 8: High-level DBN for the Student's Affect Model

In Figure 9, the DBN for a specific time is expanded; each node is decomposed in a number of nodes.

The student's knowledge of numbers factorization comes from the pedagogical student model, which models how much the student knows the factorization of the numbers included in the current game interaction.

For personality, we have two nodes based on the Five-Factor Model of Personality [Heinström 2010, Costa and McCrae 1992]. We include *conscientiousness* and *neuroticism* dimensions of personality because they have a strong relationship with learning, as has been identified in [Heinström 2010].

Goals are fundamental to understanding the affective state; we infer them from personality traits and student's knowledge, as indirect sources of evidence. There are three relevant goals: *Learning Numbers' Factorization*, *Succeeding*, and *Quick Gamming*.

The information for the *Tutorial Situation* nodes comes from the results of the student's actions. We use the knowledge the student is gaining in the game, whether he reached o did not reach the target, and how long it took for the student to reach the target.

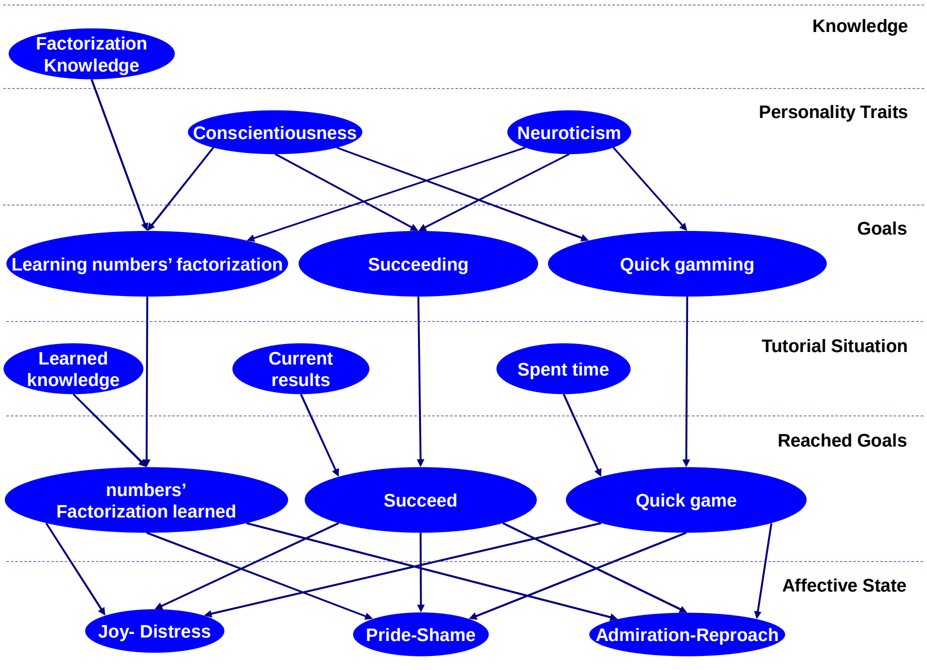

Figure 9: Detailed affective student model represented by a Bayesian network

The *Reached Goals* nodes represent whether the student achieved his goals. The student's appraisal of the current situation given his goal is represented by the relationship between the *Goals* and *Tutorial Situation* nodes through the *Reached Goals* nodes (OCC Model). The influence of the student's appraisal on the student's affect is represented by the link between *Reached Goals* nodes and *Affective State* nodes.

The affective student model includes six emotions: *joy*, *distress*, *pride*, *shame*, *admiration*, and *reproach*, taken from the OCC Model. These are represented as three pairs of mutually exclusive emotions (for the same object/event/situation): *joy-distress*, *pride-shame*, and *admiration-reproach*. Therefore, we include three nodes for the affective state.

The *joy-distress* node represents the emotions that the student can feel for the situation; i.e., he is happy because he learned, or because he reached the goal, or because he was a quick gamer.

The *pride-shame* node represents the student's emotions towards himself; i.e., he is proud because he learned the topic, or because he reached the goal, or because he reached the goal quickly.

The *admiration-reproach* node represents the emotions that the student can feel towards the tutor. The student can feel admiration for the tutor because the tutor taught him, and therefore he reached the goals. Otherwise, the student can feel reproach towards the tutor because the tutor is not teaching him.

Even though our student's affect model is based on the model defined in [Conati and Maclaren 2009], there are some differences in the information that is taken into account when the emotion is detected. For example, we use knowledge as an important component of goals while they consider interaction patterns as predictors of goals. Both models make use of psychology theories to predict goals; however, they have focused on refining the model with sensors and several empirical surveys, while we have focused on the tutor's reactions to emotions, and then we have defined an affective tutor model, see [Section 5] which reacts to students' emotions. We have already evaluated this affective tutor see [Section 6].

In the next section, we describe the second component of the Model of Affect and Learning: the affective tutor model, and provide details on how it was built.

5 Affective Tutor Model

There is increasing research on the relationship between affect and learning [Calvo and D'Mello 2011]. However, many questions remain unanswered. For example, further investigation is needed to know which emotions are relevant for learning, as well as in what ways we can use these emotions to make teaching and learning more effective. From the point of view of models and methods for testing affect, there is good advancement in research; but from the point of view of explaining the relationship between emotions and learning, there is much work to be done.

We are proposing an architecture for an affective ITS that integrates information on the affective state of students and an affective tutor model. The affective tutor model reasons with student's state and enables the ITS to respond accordingly. Thus, the tutor needs a model that establishes certain conditions to present student instruction based on the affective and knowledge student states. The integration of the proposed model with an ITS is presented in [Figure 10]; it depicts how the affective tutor model uses the affective student model to improve the students learning and affect.

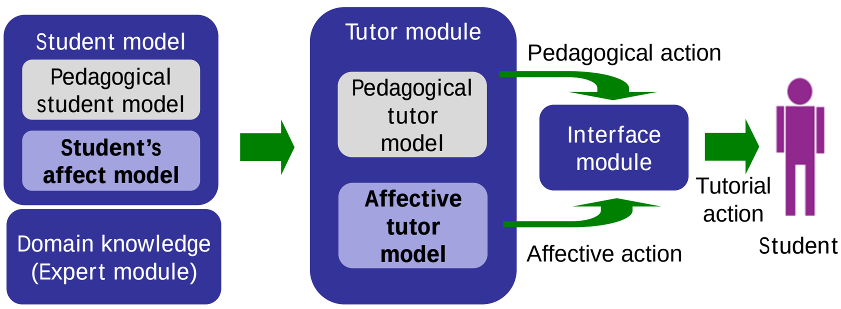

Figure 10: Affective Tutor Model

Decision theory [Clemen and Reilly 2014] provides a strong foundation to achieving the best balance between our two objectives: helping students to learn and fostering a good affective state in students. The decision process is represented as a dynamic decision network (DDN), shown in [Figure 11]. The DDN decides the tutorial action considering two utility measures, one on learning and one on affect, which are combined to obtain the global utility by a weighted linear combination. These utility functions are the means to express teachers' preferences towards learning and affect.

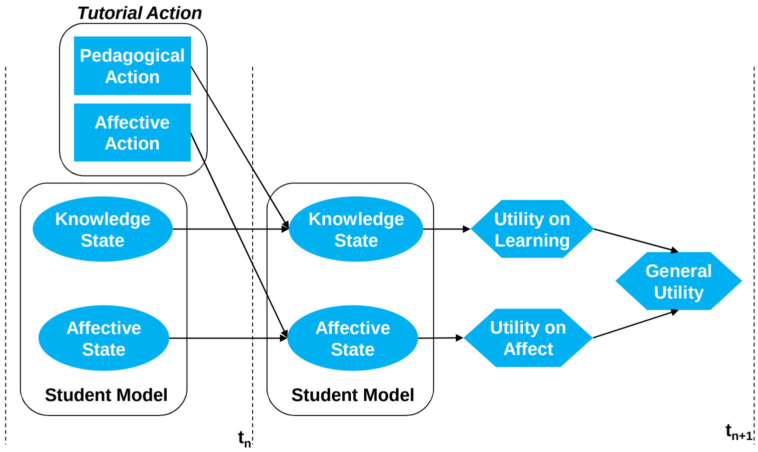

Figure 11: Dynamic decision network for the Affective Tutor Model

The DDN model includes a DBN to predict how the available tutorial actions influence the student's knowledge and affect, given his current state. This prediction is used to calculate the utility of each tutorial action for the current state.

After the student performs an action, i.e. after the student model is updated (time t_n), a new time slice is added (time t_{n+1}). At time t_n we have the current student state and the possible tutorial actions. At time t_{n+1} we have the prediction of how the tutor action influences the student's affect and knowledge. From both of these we estimate the individual and global utilities. The affective state at time t_{n+1} is assessed by the student's affect model described in the previous section. The student's knowledge is assessed by the pedagogical student model, which in the case of our study is a probabilistic model described in [Muir and Conati 2012]. The influence of each tutorial action on student's knowledge and affect, and its corresponding utility, is based on the teachers' expertise, which was gathered as described above in [Section 3].

The learning utility is measured in terms of how much the student's knowledge is improved by the tutorial action, given his current knowledge. Similarly, the affect utility is measured in terms of how much the student affect improves as a result of the action. Finally, the overall utility is computed as a weighted sum of these two utilities. Thus, the tutor calculates the utility for each tutorial action considering the current state, and selects the tutorial action with the maximum expected utility.

The decision network is not used to update the student model, but only to predict the impact of the tutorial action. At this point, the tutor delivers the selected action to the student and then uses the resulting student's action to update the student models.

The tutorial action is composed of a pedagogical component and an affective component. The pedagogical component of the tutorial action consists of textual hints, while the affective component is presented via one of Merlin animations (affective actions in [Table 5]). For example, Merlin can explain what a common factor is via text appearing in a speech bubble (pedagogical component), while making a conciliatory face and extending his arms to trigger the student's attention and motivation (affective component). The affective component of a tutorial action attempts to promote a positive affective student state and the pedagogical component aims to convey knowledge.

Figure 12 shows examples of tutorial actions; the text in the bubbles is in Spanish since we evaluate the model with Mexican kids, see [Section 6]. Examples 1-3 refer to a situation in which the student is doing well. Merlin congratulates the student by saying "Correct, these numbers do not share common factors", "Very well", or "Congratulations!" They also include animations aimed at conveying enthusiasm by playing the trumpet, showing a trophy, or clapping. Examples 4-6 refer to a situation in which the student has made a mistake. Example 4 gives a rather general verbal hint ("Think about how to factorize both your number and your partner's number"), while examples 5 y 6 provide more specific help ("Factors of a number are numbers that when multiplied gives the original number" and "A common factor is a number between two numbers without a residue"). In all cases, the tutorial actions include animations aimed at attracting the student's attention and reinforcing the verbal hints.

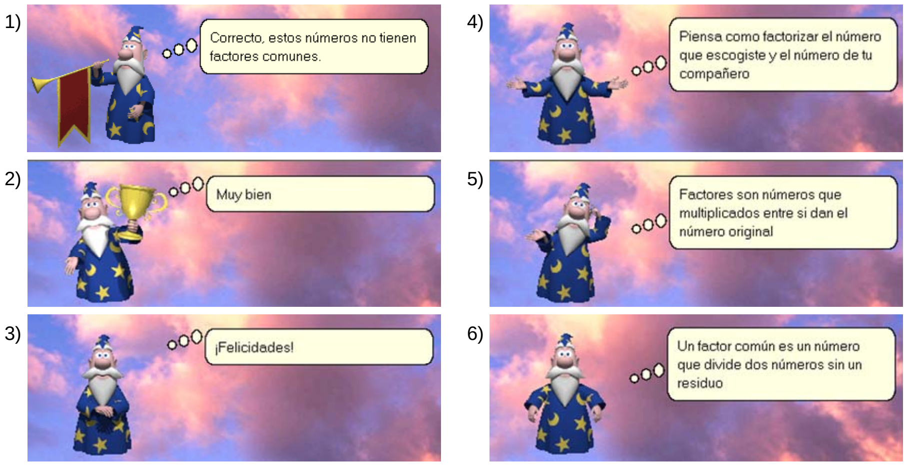

Figure 12: Examples of tutorial actions

6 Evaluation

To evaluate the performance of the Model of Affect and Learning, we conducted a user study in a school in Mexico, with students from Grade 6 of Elementary School, and 1-3 of Secondary School (Grades 6-9 of elementary school in the American system). Sixty-two students participated. To conduct this survey the hints of Prime Climb were translated into Spanish.

Each student was instructed on how to interact with Prime Climb and the game rules. In each grade, the students were randomly divided into two groups. The first group (control group) played with a version of Prime Climb that only included the model of student knowledge, and Merlin generating verbal hints with almost none of Merlin's animations; namely, the original Prime Climb. The second group played with Prime Climb with the Model of Affect and Learning (experimental group). The sizes of the different groups in our study are shown in [Table 8].

Grade		Average Age	No. of Students		
			Control Group	Exp. Group	Total
Elementary	6	11.9	8	9	17
Secondary	1	12.6	10	10	20
	2	13.8	6	5	11
	3	14.8	7	7	14

Table 8: Students participating in the study

We gave students a pre-test to evaluate their knowledge on factorization. The students then played Prime Climb for 40 minutes. They were immediately given a post-test. The pre-test and post-test took 5 minutes, on average, for a student to complete. We observed students during their interaction with Prime Climb and they also completed a questionnaire on their experience with Prime Climb after this sequence. We compared the learning gains between the control and experimental groups, shown in [Table 9]. General trends show that experimental groups did better than control groups. The maximum mark in both tests was 5 and the learning gain is absolute, it is the difference between the post-test mark and the pre-test mark.

Grade	Stat	Control Group			Experimental Group		
		Pre-test	Post-test	Gain	Pre-test	Post-test	Gain
Elem. 6	Avg	3.63	4.25	0.63	3.44	4.89	1.44
	StdDv	0.52	0.46	0.92	0.53	0.33	0.53
Sec. 1	Avg	2.80	3.00	0.20	3.10	3.60	0.50
	StdDv	1.48	1.56	2.39	1.73	1.43	1.18
Sec. 2	Avg	3.83	3.50	-0.33	3.40	3.00	-0.40
	StdDv	0.98	0.84	1.37	1.14	1.22	0.89
Sec. 3	Avg	4.29	3.86	-0.43	4.00	4.14	0.14
	StdDv	0.76	0.69	0.53	1.41	1.46	1.46

Table 9: Statistics for the control and experimental groups, per grade

However, the difference between pre-test and post-test is statistically significant only for Grade 6 for both groups, control (*p=0.041*) and experimental (*p=0.001*). The difference between learning gains in the control and experimental groups is also statistically significant only for Grade 6 (*p=0.05*). The results of the Mann-Whitney U test [Pett 1997, Levin and Rubin 1996] are shown in [Table 10]. The statistic U is calculated considering the sizes of groups (n and m) and the sum of the ranks assigned to each mark; and it is compared with the critical value for statistic u in tables [Milton 1964]. For Grade 6º $U \leq u$, therefore the difference is statistically significant in this grade.

Grd	Control Group Pre-test/post-test			Experimental Group Pre-test/post-test			Learning Gains Control Grp/Exp.Grp		
	$p(U \leq u) \leq 0.05$			$p(U \leq u) \leq 0.05$			$p(U \leq u) \leq 0.05$		
		U	u		U	u		U	u
6º	**n=m=8**	**15**	**15**	**n=m=9**	**2**	**21**	**n=8, m=9**	**16.5**	**18**
1º	n=m=10	29	27	n=m=10	31	27	n=m=10	47	27
2º	n=m=6	14.5	7	n=m=5	9.5	4	n=6, m=5	14	5
3º	n=m=7	16.5	11	n=m=7	24	11	n=m=7	20.5	11

Table 10: Mann-Whitney U Test of marks in each group: control and experimental; and between groups (Learning gains)

In general, these results seem to indicate that Prime Climb was not a good tool for students in higher grades. However, when the game was appropriate (as seems to be the case for students in grade 6) Prime Climb and our model improve learning to a significant degree. The fact that older students did not learn is not due to a ceiling effect [Hessling, Traxel and Schmidt 2004] in higher grades because students' scores were not high; that is to say, there is not a concentration of participants' score at or near the highest mark. We will perform an in-depth analysis of the interaction logs for all groups to see if we can understand why they learned differently with the game. One hypothesis is that since students in the higher grades are not tested on factorization knowledge as part of their regular curriculum, then they did not try to learn from Prime Climb as much as the students in Grade 6. For now, we have no evidence to support our intuition.

Analyzing students' reports, most students liked playing Prime Climb. The version of Merlin with animations based on the Model of Affect and Learning rated higher than the version used in the control group. Students in the experimental group stated that they found Merlin and his movements funny, and they felt that the animated character was helping them learn. Most students in the control group were not sure whether or not Merlin was helping them learn.

7 Conclusions and Future Work

We developed and tested a model for integrating affect and learning into intelligent tutoring systems. The model takes into account the affective and pedagogical states to select the best tutorial actions. The model integrates a student's affect representation and an affective tutor model.

To represent the affect of the student we adopted theoretical models of emotions and indirect sources of evidence, such as personality, goals, and results. We have attempted to build an approach that does not interfere with the students' main task. Nevertheless, we undertook to deal with the lack of direct sources of evidence, such as biological signals, through the use of a DBN.

The tutor model was designed based on teachers' expertise, and it is represented as a dynamic decision network with utility measures on learning and affect. To build the model, we surveyed skilled teachers, gathering their expertise.

We integrated and evaluated the model into an educational game to learn number factorization. We conducted a controlled user study, which showed significant improvement in learning when our model is incorporated. Students responded positively to the animated agent whose behavior is generated by considering both their pedagogical and affective state. Note that significant learning improvement only occurred when the game chosen was age and grade appropriate.

The results of our investigations are encouraging. We achieved positive feedback in evaluating the model, and we obtained higher learning gains when we used the affective model to instruct the student. The model allows intelligent tutoring systems to map a student's affective and pedagogical states to tutorial actions.

We have presented the evaluation of the Model of Affect and Learning in the math domain, but we also evaluated it in the robotics domain [Hernández, Sucar and Arroyo 2012]. We used a virtual laboratory to learn mobile robotics. In this system we conducted a Wizard of Oz evaluation to evaluate the student's affect model and the affective tutor separately. We compared the affective state reported by the students with the affective state established by the affective student model; we found that our model detects emotions with high precision. For the affective tutor evaluation, most students stated that the system with the affective agent was helping them learn [Hernández, Sucar and Arroyo 2012]. Having two test domains with positive results suggests that the model can be integrated into any ITS.

An important contribution of this work is the affective tutor model, as there are currently several investigations that infer or detect the emotions of students, but there are still no intelligent tutors which generate tutorial actions based on the affective state that are based on teachers expertise as proposed herein. On the other hand, we contribute with knowledge regarding teachers' preferences when teaching; this knowledge can be used to design surveys or educational systems. To our knowledge, there are no surveys as the one presented herein.

Even though, the results of our investigations are encouraging, we have some limitations and we need to conduct more surveys to try to probe our assumptions. For example, it would be more comprehensive whether teachers could see several students interacting with Prime Climb to give their preferences, so that they could observe different personalities, different types of gamers and different knowledge state. However, the results obtained thus far will allow us to refine the model and design other studies. The goal is to achieve a comprehensive approach to affective behavior in intelligent tutoring systems.

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