Chapter 10
Affective Tutors: Automatic Detection of and Response to Student Emotion

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Abstract. This chapter describes the automatic recognition of and response to human emotion within intelligent tutors. Tutors can recognize student emotion with more than 80%accuracy compared to student self-reports, using wireless sensors that provide data about posture, movement, grip tension, facially expressed mental states and arousal. Pedagogical agents have been used that provide emotional or motivational feedback. Students using such agents increased their math value, self-concept and mastery orientation, with females reporting more confidence and less frustration. Low-achieving students—one third of whom have learning disabilities—report higher affective needs than their higher-achieving peers. After interacting with affective pedagogical agents, low-achieving students improved their affective outcomes and reported reduced frustration and anxiety.

10.1 Introduction

Affect is a central component of human cognition and strongly impacts student learning (McQuiggan et al. 2008; Goleman 1995; Efklides and Petkakim 2005; Brand et al. 2007). If computers are to interact naturally with humans, they must recognize affect and express social competencies. Affect has begun to play an important role in intelligent tutors (Conati and MacIaren 2004; D'Mello et al. 2007) and affective tutors seem to increase the effectiveness of tutorial interactions and, ultimately learning. The field of affective tutors investigates techniques for enabling computers to recognize, model, understand and respond to student emotion effectively. One obvious next frontier in computational instruction is to systematically examine the relationships between student affective state and learning outcomes (Shute 2008).

While early learning theories ignored the importance of emotion in learning, recent research has created a link between emotion and learning and the claim has been made that cognition, motivation and emotion are the three components of

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learning (Snow et al. 1996; D'Mello et al. 2007). Various classroom studies have linked interpersonal relationships between teachers and students to increased student motivation over the long term (Wentzel and Asher 1995; Royer and Walles 2007).One goal of affective computers is to recognize affect or identify the affective state of people from a variety of physical cues that are produced in response to affective changes in the individual (Picard et al. 2004).

When humans use affect within one-to-one teaching relationships, the result is very powerful. For example, in their research on 'thin slices,' Ambady and Rosenthal demonstrated that based on a short segment of video, as little as six seconds of a teacher's first interactions with a student, participants could predict that teacher's effectiveness and student end-of-term grades based on the teacher's exhibited use of affect (Ambady and Rosenthal 1992). Wentzel (1997) has shown that caring bonds between middle schoolchildren and their teachers are predictive of learners' performance. This chapter looks at the role new technology plays in automatic recognition of and response to student affect. Affective interventions encourage learning, lessen student humiliation and provide support and motivation that outweighs or distracts from the unpleasant aspects of failure. Section 2 describes real-time automatic recognition of emotions exhibited during learning, while Section 3 describes attempts to automatically generate appropriate responses to student emotion. Section 4 describes ways to evaluate these recognition and response mechanisms and to integrate them into educational practice. This research is based on efforts at the University of Massachusetts, Arizona State University and the MITMedia Lab.

10.2 Automatic Recognition of Student Affect

Great interest exists in embedding affective support into tutoring applications and research has focused on automated detection of affective states as a first step towards this goal (Conati and Mclaren 2004; D'Mello and Graesser 2007; McQuiggan and Lester 2006; Graesser et al. 2007). Currently there is no gold standard for either labeling a person's emotional state or for responding to it. One approach to recognizing emotion is to triangulate among three different inputs: sensor data, student self-reports, and human observation of students. While we accept that there will never be definitive categorization of a human's emotional state, this triangulation has been used Arroyo et al., to identify clear examples of emotions (frustration, flow, etc.) that can be labeled using sensor information (Woolf et al. 2009).

Hardware sensors have the potential to provide information on students' physiological responses that have been linked to various affective states (D'Mello and Graesser 2007; Graesser et al. 2007; D'Mello et al. 2007). Research explores various sensors' potential for affect recognition, e.g., Burleson, 2006 developed a learning companion that depended on a sensor framework (incorporating a mouse, posture chair, video camera, skin conductance bracelet) to recognize and respond to student affect. Our sensor platform of four physiological sensors (Fig. 10.1) has been tested with more than 1,000 students in middle high and college classes. The platform is unobtrusive enough to be used by students in a typical setting and resource-conscious enough to run on average computer labs available to students

(Cooper et al., 2009). These sensors collect raw data about physical activity and state of a student and the challenge remains to map this data into models of emotional states and use this information productively.

Mental State Camera. We use a standard web-camera to obtain 30 frames per second at 320x240 pixels. This is based on an earlier facial expression recognition system used in Burleson's Affective Learning Companion (Mota and Picard 2003; Kapoor et al. 2007. The present system is coupled with El Kaliouby's MindReader applications (el Kaliouby 2005). We developed a Java Native Interface (JNI) wrapper around the MindReader library. The interface starts a version of the MindReader software, and can be queried at any time to get the most recent mental state values that have been computed by the library. In the version used in the experiments, only the six mental state features were available, but in future versions we can train it on new mental states.

Fig. 10.1 Sensors used in the classroom (clockwise): mental state camera, skin conductance bracelet, pressure sensitive mouse, pressure sensitive chair.

Skin Conductance Bracelet. The Affective Computing Group at the MIT Media Lab has been advancing the development of wireless wearable skin conductance sensors for over a decade. Various implementations include the galvactivator, a glove that could illuminate an LED when its user had heightened levels of skin conductance (Picard and Scheirer 2001); HandWave which used a custom built Printed Circuit Board (PCB) and 9V battery to provide blue tooth wireless transmission of skin conductance data at rates up to5 Hz (Strauss et al. 2005).

The current system used in our research employs the next generation of Hand Wave electronics developed at MIT, providing greater reliability, lower power requirements through wireless RFID transmission, and a smaller form. This smaller form was redesigned to minimize the visual impact and increase the wearable aspects of previous versions. We integrated and tested these electronic components into a wearable package suitable for students in classrooms.

Pressure Sensitive Mouse. The pressure mouse was originally developed by the Affective Computing Group at MIT. It uses six pressure sensors embedded in the surface of the mouse to detect the tension in users' grip and has been used to infer elements of users' frustration(Qia and Picard 2002; Dennerlein et al. 2003). We replicated MIT's pressure mouse through a production of 30 units. The new design minimized the changes made to the physical appearances of the original mouse in order to maintain a visually non-invasive sensor state.

Pressure Sensitive Chair. We used a simplified posture state chair developed at ASU using a series of eight force sensitive resistors as pressure sensors dispersed throughout the seat and back of a readily available seat cover cushion. This posture chair sensor was developed at ASU.

In our framework, each feature source from each student is a separate stream of data. Hence we have streams of data that each report asynchronously and at different rates. In order to merge all of the data sources, an ID from each student, and a time of the report was needed from each source. We have a database table with a row for every time stamp and wrist ID pair, and a column for each reported sensor value and tutor data value. Each cell in a row represents the latest report of the data source.

10.3 Automatic Response to Student Affect

Once a student's emotion has been recognized, the next issue is to identify how to respond to improve student motivation and learning. Providing empathy or support strongly correlates with learning (Graham and Weiner 1996; Zimmerman 2000) and the presence of someone who cares, or at least appears to care, can be motivating. Various studies have linked interpersonal relationships between teachers and students to motivational outcomes (Wentzel and Asher 1995; Picard et al. 2004). Can this noted human relationship be reproduced, in part, by apparent empathy from a computer character? Apparently the answer is yes (Bickmore and Picard 2004). People seem to relate to computers in the same way they relate to humans and some relationships are identical to real social relationships (Reeves and Nass 1998). For example, students continue to engage in frustrating tasks on a computer significantly longer after an empathetic computational response (Klein et al. 2002), have immediately lowered stress level (via skin conductance) after empathy and after apology (Prendinger and Ishizuka 2005), and relational skills improve long-term ratings of caring, trust, respect, desire to keep working (Bickmore and Picard 2004). Computer agents impact student learning, affect and motivation based on gender, ethnicity and realism of the agent (Baylor 2005).

This is not to say that the inferences, movements and interventions of computer agents can exactly replicates those of people, nor can peer theories exactly map to

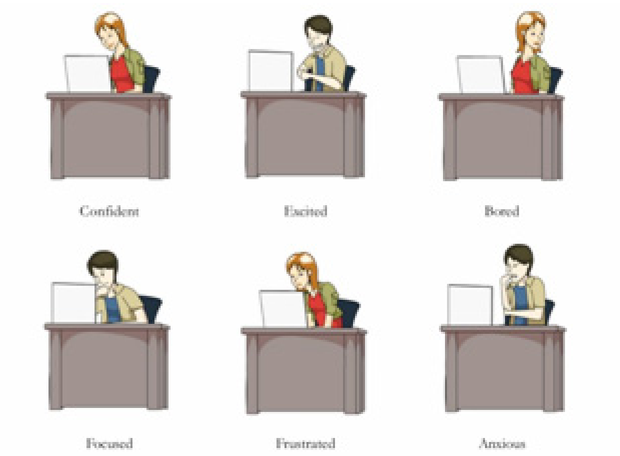

Fig. 10.2 Pedagogical Agents act out their emotion and talk with the student expressing full sentences of cognitive, meta-cognitive and emotional feedback.

the human peer-tutoring case; however, computer control does allow for careful testing of hypotheses about how to use virtual peer support for learning (Fig. 10.2) (Picard et al. 2004).

Peer learning companions can create adaptable vicarious experiences for students (Burleson and Picard 2008; Baylor 2005; Chan and Baskin 1990). Companions can create adaptable vicarious experiences that are difficult to create in classrooms and observation of peers succeeding may enhance the observing student's self-efficacy (McQuiggan et al. 2008). Verbal persuasion is a common motivational tool used by tutors both human and automated (Lepper et al. 1993). Companions that express confidence in a student's abilities can have profound effect on the student's own self-efficacy beliefs. The impact is determined by the value the student places on the persuader, so an established relationship between tutor and the student makes verbal persuasion all the more powerful (McQuiggan et al. 2008).

One goal of modeling and responding to student affect is to impact the student's affective state and subsequent changes in student physiology (Bandura 1997). Research has shown that strategies that guide students toward affective states with lower arousal levels will diminish the adverse effects of high-arousal physiological responses on student efficacy. Affect recognition can use pedagogical companions to take action when situations of arousal and low self-efficacy occur (McQuiggan et al. 2008).

10.3.1 Learning Companions

We describe gendered learning companions that provide support and encouragement, emphasizing the importance of perseverance, expressing emotions and offering strategies (e.g., "Use the help function"), see Fig. 10.3 (Arroyo et al 2009;

Cooper et al. 2009). These learning companions (LCs) are *empathetic* in that they visually reflect the last emotion reported by the student (queried within the system every five minutes); as long as that emotion is not negative, e.g., companions do not mirror frustration or boredom. Companions act out their emotion and talk with students expressing full sentences of meta-cognitive and emotional feedback. They are non-intrusive — they work on their own computer to solve the problem at hand, and react only after the student has answered the question. Agents respond with some of Carole Dweck's (2002) recommendations about disregarding success and valuing effort. This adds a new dimension to the traditional feedback regarding success/no-success generally given to students.

We measured the impact of LCs on student motivation and achievement and integrated controlled exploration of their communicative factors (facial expression and mirroring postures) as the student/agent relationship developed. Empirical studies show that students who use LCs increased their math value (e.g., questions such as "Mathematics is an important topic"), self-concept (e.g., "I am good in mathematics") and mastery orientation, see Sections 10.4.4-10.4.5. Students tend to become more bored (less interested) towards the end of any instructional session. Yet students using LCs maintain higher levels of interest and reduced boredom after 15 minutes of tutor use. They reported a higher mean confidence, interest and excitement. Despite the fact these results were not significant, this relative advantage for LCs indicates that they might alleviate students' boredom as the session progresses.

10.3.2 Automatics Affective Response

The learning companions used in Wayang (see Section 10.4) deliver approximately 50 different messages emphasizing the malleability of intelligence and the importance of effort and perseverance (Table 10.1). The messages also include meta-cognitive help related to effective strategies for solving math problems and effective use of Wayang's tools. Ultimately, the interventions will be tailored according to Wayang's affective student model. However, we are currently still validating the models and algorithms for deciding which intervention to provide and when, and thus relied on an effort model only to assign messages for this experiment. This section describes these interventions including *attribution* and *strategy* training, as well as *effort affirmation*.

The affective support was to train students motivationally, by emphasizing the importance of effort and perseverance and the idea that intelligence is malleable instead of a fixed trait (Dweck 2002). The characters provided this support by responding to the effort exerted by students rather than to the student's emotions. Characters were either unimpressed when effort was not exerted, or simply ignored that the student solved the problem. They also offered praise to students who exerted effort while problem-solving, even if their answers were wrong, highlighting that the goal is to lessen the importance of performance in favor of learning.

Table 10.1 Companions provided several responses based on student effort

Type	Sample message
Attribution (General)	I found out that people have myths about math, thinking that only some people are good in math. Truth is we can all be good in math if we try.
Attribution (Effort)	Keep in mind that when we are struggling with a new skill we are learning and becoming smarter!
Attribution (No Effort)	We will learn new skills only if we are persistent. If we are very stuck, let's call the teacher, or ask for a hint!
Attribution (Incorrect)	When we realize we don't know why the answer was wrong, it helps us understand better what we need to practice.
Effort Affirmation (Correct No-effort)	That was too easy for you. Let's hope the next one is more challenging so that we can learn something.
Effort Affirmation (Correct Effort)	Good job! See how taking your time to work through these questions can make you get the right answer?
Strategic (Incorrect)	Are we using a correct strategy to solve this? What are the different steps we have to carry out to solve this one?
Strategic (Correct)	We are making progress. Can you think of what we have learned in the last 5 problems?

The characters were highly positive, in the sense that they displayed encouraging gestures (e.g., excitement and confidence). Negative gestures (appearing frustrated or bored) were not effective and were eliminated by researchers. Characters behaviorally mimicked student self-reported emotions, which is a form of a non-verbal empathetic response (e.g., learning companions appeared excited in response to student excitement, see Fig. 10.3, right). In this experiment the companions occasionally expressed non-verbal behaviors of positive valence only, the underlying goal being to make them appear life-like and engaged and to impart some of their enthusiasm to the students. The next three types of interventions described are verbal messages tailored according to the tutors modeling of students' effort.

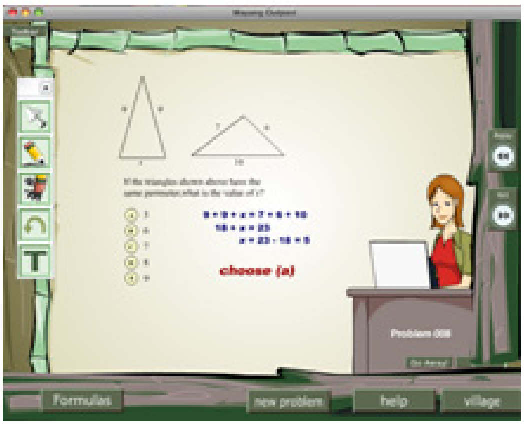

Fig. 10.3 The Wayang Tutor with Jane, the female affective learning companion

Attribution Interventions. Attribution theory proposes that students' motivation to learn is directly rooted in their beliefs about why they succeed or fail at tasks (Weiner 1972). If students can be taught to alter these beliefs, for instance to understand that failure is the result of a lack of effort instead of a lack of ability, then their motivation to learn and learning outcomes can be significantly improved (Robertson, 2000). For example:

- *General attribution* messages encourage students to reflect about myths and math learning in general;
- *Effort attribution* messages reinforce that effort is a necessary by-product of learning, and are specially tailored to situations where students are investing effort but are struggling;
- *No-effort attribution* messages are more emphatic than effort attributes and are designed to help students realize that effort is necessary to learn, and generated when students are not investing effort;
- *Incorrect attribution* messages are generated to motivate students after they provide an incorrect response, by re-formulating how they perceive errors.

Effort-Affirmation Interventions. In contrast to the effort-attribution messages described above, which aim to change students' attitude towards effort during problem solving and are generated before the student actually starts problem solving, *effort-affirmation* interventions acknowledge effort after students obtain a correct solution (see Table 10.1 for examples). These interventions include:

- *Correct no-effort interventions* are generated after a student invests no effort but obtains a correct solution, to make students realize that praise is not appropriate;
- *Correct-effort affirmations* are generated after a student both invests effort and obtains the correct solution, to acknowledge the student's effort.

Strategic Interventions. The final type of intervention focuses on meta-cognitive strategies, with the goal of both making students more effective problem solvers and motivating them for learning in general.

- *Incorrect strategic* messages are generated when students are not succeeding at problem solving, to motivate them to change their general problem-solving strategy, i.e., think about why they are not succeeding;
- C*orrect strategic* messages are generated when students are succeeding at problem solving, to encourage them to evaluate their progress.

10.4 Experiments with Affective Tutors

The affect recognition and response software described above are stand-alone; they can provide affective input to any tutor and can generate its responses for any tutor. We conducted several empirical evaluations with this software to directly connect several objectives of affect research. First we describe experiments that dynamically identified student emotion during learning and reliably identified these emotions through classifiers. Then we describe experiments to personalize tutor response based on student needs and to integrate this work into educational practice.

Currently we are using affect systems in tandem with Wayang Outpost, a multimedia tutoring system for high school geometry and algebra; see Figure 10.3 (Arroyo et al., 2007; 2009; Woolf et al., 2010). Problems are presented one at a time, each consisting of the problem statement with four or five solution options directly below it. Students select an answer and the tutor provides immediate visual feedback by coloring the answer green or red, for correct or incorrect respectively. Prior to or after selecting an answer, a student may ask for a hint, which Wayang displays in progression from general suggestions to the correct answer. In addition to this domain-based help, Wayang includes a wide range of metacognitive and affective support, delivered by learning companions; agents designed to act like peers who care about the student's progress, and offer support and advice on how to improve student learning strategies. Within each topic section, Wayang adjusts the difficulty of problems provided depending on past student performance.

Gendered and ethnically diverse companions allow exploration of how the gender and ethnicity of companions influences outcomes (e.g., learning, attitudes) (Arroyo et al. 2009). The learning companions' interventions are tailored to a given student's needs according to two models of affect and effort embedded in the tutor. The *effort* model uses interaction features to provide information on the degree of effort a student invests in generating a problem solution. An *affect* model assesses a student's emotional state; based on linear regression, this model is derived from data obtained from a series of studies described in (Arroyo et al. 2009; Cooper et al. 2009). Wayang has been used with thousands of students in the past and has demonstrated improved learning gains in state standard exams (Arroyo et al. 2008; 2009)

10.4.1 Methodology for the Affect Studies

We conducted several series of experiments involving the use of sensors, learning companions and Wayang Outpost (Arroyo et al., 2009; 2010). One study involved 35 students in a public high school (HS) in Massachusetts; another involved 29 students in the University of Massachusetts (UMASS); and the final study involved 29 undergraduates from Arizona State University (AZ). In the HS and UMASS studies, students used the software as part of their regular math class for 4-5 days and covered topics in the traditional curriculum. In the AZ lab study, students came into a lab for a single session. These three experiments yielded the results of 588 Emotional Queries from 80 students who were asked about their emotion, e.g., "How confident do you feel?" The response was a scale 1-5 and the queries separated into four emotion variables: 149 were about confidence/anxiety, 163 about excitement/depression, 135 about interest/boredom, and 141 about frustrated/not frustrated. 16 of the student responses gave no answer to the Emotional Query. Models were created to automatically infer student emotions from physiological data from the sensors. Students produced self-reports of emotions and all queries include valid data from at least one sensor.

Another set of studies quantitatively analyzed the benefit of learning companions on affective and cognitive outcomes. The subjects included one hundred and eight (108) students from two high schools 1 (one low and the other high achieving) in the state of Massachusetts and involved 9th and 10th graders. Two thirds of the students were assigned to a learning companion of a random gender, and one third to the no learning companion condition. We obtained complete data (pre and posttest survey and math test) for a smaller subset of subjects. Students took a mathematics pretest before starting, and completed a survey that assessed their general attitude towards mathematics.[1]The pretest covered general attitudes towards math and learning, such as likes/dislikes of math, how much was math valued as important, and how students felt when they solved math problems (anxiety, confidence, frustration, boredom, excitement). Four questions asked about student feelings towards problem solving before they began to work with the tutor, including interest/boredom, frustration, confidence/anxiety, excitement (e.g. how frustrated do you get when solving math problems). For the next three days, students used the Wayang instead of their regular mathematics class. Approximately every five minutes, students were asked to provide information on one of the four target emotions (e.g. how frustrated do you feel?). At the start of a student's interaction with Wayang, learning companions introduced themselves and when students needed help during problem solving, the companions reminded students about the "help button," which provided multimedia based support in the form of animations with sound. Characters spoke out the messages as described in the previous section, occasionally at the beginning of a new problem or after a correct or incorrect attempt to solve the problem. After students used the tutoring module for three days, they took a mathematics post-test, and answered the same questionnaire they had received prior to using the tutor. In addition, the post-survey included five questions about the student's perceptions of the Wayang tutoring system (*Did you learn? Liked it? Helpful? Concerned? Friendly?*). Several student behaviors were logged, e.g., success at problem solving and use of tools and help. Students' self-report of their emotions within the tutor were logged, as well as students behavior, e.g., muting the characters (using a mute button), and whether they abused help or quick-guessed.

10.4.2 Automatic Affect Recognition Empirical Studies

Using the four sensors described in Section 10.2 and placed on each student's chair, mouse, monitor, and wrist, information was conveyed to the tutor about student posture, movement, grip tension, arousal, and facially expressed mental states. Experiments showed that when sensor data supplemented a user model based on tutor logs, the model reflects a larger percentage of the students'

[1] The pre-test included 3 items for self-concept in math ability, e.g., students compared themselves to other students in their math ability and compared mathematics to other subjects; 3 items to address subjective mathematics liking/value).

self-concept than does a user model based on the tutor logs alone. The models were further expanded to classify four ranges of emotional self-concept including frustration, interest, confidence, and excitement with over 78% accuracy. We used stepwise regression analysis with each of the emotions as the dependent variable, and tutor and sensor features as the independent variables. Results from the regression show that the best models for the emotions confidence, frustration, and excitement came from the subset of examples where all of the sensor data was available, and the best model for interested came from the subset of examples with mouse data available.

Table 10.2 shows that the best classifier of each emotion in terms of Accuracy ranges from 78% to 87.5%. By using Stepwise Regression we have isolated key features for predicting user emotional responses to four categories of emotion. These results are supported by cross validation, and show improvement using a very basic classifier.

Table 10.2 This table shows the results of the best classifier of each emotional response. Accuracy of no classifier is a prediction that the emotional state is not high. Values in parentheses include the middle values in the testing set as negative examples.

Classifier	True Pos.	False Pos.	True Neg.	False Neg.	Accuracy (%)	Accuracy (%) No Classifier
Confident All	28(28)	5(24)	10(16)	1(1)	86.36(63.77)	34.09(57.97)
Frustrated All	3(3)	0(0)	46(58)	7(7)	87.5(89.7)	82.14(85.29)
Excited Wrist	25(25)	9(37)	25(40)	5(5)	78.1(60.7)	53.12(71.96)
Interested Mouse	24(25)	4(19)	28(53)	7(7)	82.54(74.76)	50.79(69.90)

This affect recognition evaluation made several important contributions to the field of sensor recognition of student affect in intelligent tutors. We showed that students' self-reports of emotion can be automatically inferred from physiological data that is streamed to the tutoring software for students in real educational settings. Summaries of this physiological activity, in particular data streams from facial detection software, can help tutors predict more than 78% of the variance of students emotional states, which is much better than when these sensors are not used (Table 10.2). We analyzed how students feel and behave while solving mathematics problems in a public school setting and identified state-based fluctuating student emotions through student's self-reports. These fluctuating student reports were related to longer-term affective variables (e.g., value mathematics and self-concept) and these latter variables, in turn, are known to predict long-term success in mathematics, e.g., students who value mathematics and have a positive self-concept of their mathematics ability perform better in mathematics classes (Zimmerman 2000). An opportunity exists for tutoring systems to optimize not only learning, but also long-term attitudes related to students' emotions while using the software. By modifying the "context" of the tutoring system including students' perceived emotion around mathematics, a tutor might optimize and improve their mathematics attitudes.

10.4.3 Automatic Response to Affect Results

The sensor data described above provides emotional predictions that are a first step for intelligent tutor systems to create sensor based personalized feedback for each student in a classroom environment. While many researchers have created affective agents, e.g., (Baylor 2005; Lester et al. 1999), evaluation of their impact on learning has not been conclusive.

Our studies targeted several population demographics. First we evaluated the differences between male and female approaches to learning with the tutor. Second we focused on low–achieving students particularly students with learning disabilities. For each of these populations, we evaluated students' affect and cognition both before and after using the tutor. Within each population, we additionally examined high school (HS) and undergraduate (UG) populations, which can be summarized as follows. HS students had less math incoming ability than UG. Students in the HS study were more "pessimistic" than the UG study, both in pretest surveys and self-reports of emotions, while UG students were not generally frustrated, HS students reported more frustration, and less interest, confidence and excitement. The combination of both populations provided an interesting mix of students with different feelings and math abilities. Both populations learned based on post-pre test tests; they improved an average 10% in math performance (25% proportional learning gain). The details of our gender studies and evaluation of students who are low achieving continues below.

Table 10.3 Significant Post-Tutor Outcomes: Main and interaction effects for Affective and Cognitive Outcomes. Key: H-A—High-Achieving students; L-A –Low-Achieving students; LC —Learning Companions;∅— No significant difference across conditions; ∅ MathAbility —No significant MathAbility effect or MathAbilityxLC interaction effect

	Overall Effect	**Targeted and Differential Effects by Gender and Achievement Level**
Learning	Students learned in all conditions (paired samples t-test, $*t(99) = 2.4$, $p = .019$), but no significant effect for LC	L-A students improved more than H-A in all conditions $*F(99,1) = 5.3$, $p = 0.02$
Perceptions of the Tutor	∅	Females using LCs have higher perception of the tutor $**F(50,1)=7.5$, $p=.009$; Males not using LCs have a higher perception of the tutor $**F(94,1)=10.5$, $p=.002$
		H-A students perceive the tutor better than L-A when LCs are absent, LCxMathAbility $**F(96,1)=6.84$, $p = 0.01$
Liking of Mathematics	Students receiving Female LC demonstrated higher math liking. $*F(93,2) = 3.7$, $p = 0.03$	∅ MathAbility
Math Ability Self-concept	Students receiving Jane showed higher posttest self-concept. $*F(94,2) =3.6$, $p = 0.03$	When LCs are absent, H-A students had higher increase in self-concept than L-A. LCxMathAbility: $^{+}F(94,3) = 2.3$, $p = .08$

We carried out Analyses of Covariance (ANCOVA) for each of the affective and behavioral dependent variables (post-tutor and within tutor) shown in Table 10.2.

Table 10.4 Significant emotion within and after using the tutor. Key: **LC**–Learning Companions; H-A—High Achieving; L-A –Low Achieving; ∅—No significant difference across conditions; **∅MathAbilityxLC**—No significant MathAbilityxLC interaction effect/MathAbility effect.

	Overall Effect	**Targeted Effect by Gender and Achievement Level**	**DifferentialEffect by Gender and Achievement Level**
Frustration	Students with female companions reported less overall frustration **F(213,2) = 6.1, p =.003	Females using the female companion have less frustration, within tutor: ***F(99,2) = 8.2,p = .001 After tutor: $^{+}$F(49,1) = 3.1, p = 0.09 L-A students have lower post-tutor frustration in the LC condition than no-LC. $^{+}$F(58,1) = 3.4, p=.07	When LCs are absent, L-A students have higher post-tutor frustration than H-A. LC x MathAbility $^{+}$F(93,3) = 2.4, p = .08
Confidence	Students using LCs have higher overall confidence, within tutor: *F(204,1) = 5.3, p = .02	Females using the female companion have more confidence, within tutor: **F(96,1) = 5.6,p = .01 L-A students in the LC condition have higher confidence. Within Tutor LC effect: **F(108,1)= 7.3, p = .008 Post-tutor LC effect: *F(56,1)= 3.8, p = .05 and	H-A students have higher confidence than L-A students (but esp. when companions are absent) MathAbility effect within: *F(204,1)= 4.1, p = .05 MathAbility effect posttutor: *F(91,1) = 5.8, p = .02
Interest	Students in the LC condition have higher overall interest at posttest time. LC main effect: $^{+}$F(94,1) = 3.4, p = .07	L-A students in the LC condition report marginally more post-tutor interest. LC main effect: $^{+}$F(58,1) = 2.7, p =.1	L-A students report more boredom than H-A students across all conditions MathAbility effect $^{+}$F(219,1) = 2.9, p = .09
Excitement	∅	Females using the female companion report more excitement. After tutor: $^{+}$F(53,1) =3.2, p = 0.08	Females report less excitement than males with no LC, within tutor, GenderxLC: *F(200,1) = 6.1,p = .02 Post-tutor, GenderxLC: *F(67, 1) = 5.3, p = .02 H-A students report less excitement when LCs are absent, no difference when LCs are present. MathAbilityxLC within: *F(200,1) = 5.2, p=.02
Productive behavior: time in hint problems	∅	L-A students spend more time in hinted problems with LCs. $^{+}$F(67, 1) = 2.9, p = 0.095	Females spent more time than males on “helped problems” in the LC condition, within tutor, Gender xLC: $^{+}$F(109,1) = 2.78, p = 0.09
Gaming Behavior; Quick-guess. Help abuse	∅	Females using companions made fewer quick guesses by females in LC condition. Mean guesses per student: **F(55,1) = 7.4, p = 0.009	Females abused help marginally less, across all conditions. Gender: $^{+}$F(110,1) = 2.9, p = 0.09 Females made fewer quick-guesses with LCs; males made more quick guesses with LC: GenderxLC **F(109,1) = 9.03,p = 0.003 L-A students quick-guess more than do H-A students MathAbility effect: **F(109,1) = 5.9, p = 0.017 No MathAbilityxLC interaction effect

Table 10.3 shows the results for general post-tutor outcomes, while Table 10.4 presents the results for affect-related and other variables measured within the tutor. As far as emotions, we include findings both on students' self-reported emotions within the tutor, and post test differences in survey responses (note that in Table 10.2, we reported how students were feeling *before* they interacted with Wayang, while Tables 10.3 and 10.4 look at how interaction with Wayang influenced these feelings).

Our covariates consisted of the corresponding pretest baseline variable (e.g., we accounted for students' pretest baseline confidence when analyzing confidence while using the tutor or afterwards). Independent variables corresponded to *condition*, specifically learning companion (LC) present vs. absent and LC type (Female (Jane) vs. Male (Jake) vs. no-LC). We analyzed both main effects and interactions for achievement level (MathAbility) and conditions over all student data (see second and last columns of Tables 10.3 and Table 10.4). In addition, because of the special affective needs of the targeted group (e.g., females or low-achieving), we repeated the ANCOVAs for that population only, for a "targeted effect," Table 10.4 (third column). Results showed that all students demonstrated math learning after working with Wayang, with low-achieving students learning more than high achieving students across all conditions (Table 10.3). Learning companions did not affect student learning directly, but successfully induced positive student behaviors that have been correlated to learning, specifically, students spent more time on hinted problems (Arroyo and Woolf 2005) (see "Productive behavior" row, Table 10.4). The beneficial effect of learning companions was mainly on affective outcomes, particularly on confidence (see "Confidence" row, Table 10.4). Low-achieving students who received learning companions improved their confidence while using the tutor and at post test time more than students with no learning companions, while their counterparts in the no-LC condition tended to decrease their confidence (Table 10.4).

10.4.4 Gender Studies

While learning companions afford affective advantages for all students, several significant effects in the ANCOVAs indicated a higher benefit of learning companions for female students. In the case of the emotional outcomes just mentioned (confidence and frustration, in particular), the effects are stronger for females than for males (i.e. while all students improved their confidence and reduced their frustration, the third column of Table 10.3 shows stronger significance for females alone). Last column of Table 10.3 also shows that females' confidence is improved but not confidence for males. It is important to note that these gender effects on emotions (within or after the tutor) are not due to females starting out feeling worse, as our analyses account for that baseline pretest emotion as a covariate.

Females especially perceived the learning experience with Wayang significantly better when learning companions were present, while the opposite happened for males, who actually reported worse perceptions of learning when learning companions were present. Female students in the LC condition also had more productive behaviors in the tutor: they spent more time than did males on “helped problems” compared to females in the no-LC condition; they “gamed” less when characters were present (a significant interaction effect revealed that the opposite happens for males).

10.4.5 Behavior of Students with Low Achievement

Currently, students with learning disabilities (LD) who require extra resources comprise 13% percent of students in USA (NCES 2009). These students show improved performance with certain classroom interventions (e.g., providing extra time on tasks, peer tutoring). However these interventions are difficult or impossible to sustain in classrooms without additional instructional support, something that schools are increasingly unable to provide due to budgetary constraints. To the extent that these students are not being educated to their full potential, there is a large negative impact not only in the lives of these students but on society at large.

The under-achievement of students with LD in math does appear to have a biological basis, and there is evidence that many of these students have difficulties with working memory, executive control and procedural knowledge (Geary et al. 1999; 2007). As a result, many students with LD may persist in using counting strategies (e.g., finger counting) long after their typically achieving peers have switched to retrieving answers from memory (Fletcher et al. 2007), taking longer to solve math problems and performing poorly in math class and high-stake tests (Olson 2005). Students with LD develop more negative feelings towards math, choose less advanced math classes in high school and are later under-prepared for science and math careers. LD is a complex multi-factor problem and most educational institutions do not have the tools needed to provide cost-effective instruction tailored to each individual.

Table 10.5 Affective self-reports of high-achieving vs.low-achieving students prior to tutoring

Affective Criterion	**Means, standard deviations and between-subjects test** Low-achieving: N=64; High-achieving: N=43
Self-concept of math ability (in comparison to other students, other subjects, 3 items)	Low-achieving: M=3.2 SD=1.1 High-achieving: M=4.1 SD=1.0 *****F(106,1)=18.2, p=.000**
How confident do you feel when solving math problems?	Low-achieving: M=3.1 SD=1.3 High-achieving: M=4.0 SD=1.3 *****F(105,1)=11.5, p=.001**
How frustrating is it to solve math problems?	Low-achieving: M=3.6 SD=1.2 High-achieving: M=3.0 SD=1.1 **** F(106,1)=7.6, p=.007**
How exciting is it to solve math problems?	Low-achieving: M=2.2 SD=1.2 High-achieving: M=2.7 SD=1.4 ***F(106,1)=3.64, p=0.05**

Low-achieving students were defined as those who scored lower than median grade on the math pretest. One third of these low-achieving students had been previously diagnosed as having a specific learning disability in math or reading and had an Individualized Education Plan (IEP), a document that identifies a student's academic, physical, social and emotional needs. Most students with IEPs (95%) are part of this low-achieving group. Table 10.5 shows that low-achieving students disliked math more, valued it less, had worse perception of their math ability, and reported feeling worse when solving math problems. Since low achieving students (both with and without disabilities) struggle with math, our conjecture was that *all* low achievers could require additional affective support. Thus, the first goal of the study was to examine the affective needs of both low achieving and learning disability students in our data (15% of subjects).

10.4.6 Discussion of Results for Low-Achieving Students

Learning companions had a positive impact for all students on some measures, e.g., all students receiving the female companion (Jane) improved math liking and self-concept of their math ability. This was not the case for the male learning companion (Jake), which was muted by students twice as much as Jane, making it too similar to the control version.

Some differential effects (last column Table 10.4) suggest that learning companions are essential for low-achieving students' affect. When LCs are present, low achieving students report positive affect nearly as much as do high-achieving students and it is only when learning companions are absent that a large gap exists between these student groups. This affective gap reduces when learning companions are present. This result is found for several outcome variables: self-concept, perceptions of learning, frustration, excitement.

However, learning companions did not manage to change some negative feelings and behaviors: low-achieving students did quick-guess more across all conditions than high achieving students; low achievement students reported less interest than high achieving in all conditions. We did see an increase in productive behaviors that lead to learning (Arroyo and Woolf 2005), low-achieving students spent more time in problems where help is requested (i.e. students pay more attention to hints).

General implications for tutors include the possibility of defining features and tool sets that support low-achieving students differentially from the rest. In future studies we will analyze separately the impact of companions on a large population of students with learning disabilities, compared to students without learning disabilities.

10.4.7 Discussion of Gender Studies Results

Overall effects in Tables 10.3 and 10.4, second column, suggest a general advantage of learning companions (both Jane and Jake) for some affective outcomes. Table 10.3 shows that students reported significantly <u>less frustration and more interest</u> (less boredom) when learning companions were used compared to the no learning companion condition. At the same time, Table 10.4 shows that students receiving the female learning companion reported significantly higher self-concept and liking of math at posttest time. Students receiving Jane also reported higher confidence towards problem solving and in post-tutor surveys. One reason why Jake was at a disadvantage compared to Jane might be the fact that the male character was muted twice as much as was the female character. If students mute the characters, then the experimental condition turns out to be highly similar to the control condition (no learning companion) thus diminishing its effect. While significant results are limited to affective outcomes —learning companions did not impact learning—we are impressed given the short exposure of students to the tutoring system.

10.5 Discussion and Future Work

This chapter described both automatic recognition and automatic response to student affect within intelligent tutors and provided examples of such systems that contribute to the growing body of work on affective reasoning for intelligent tutoring systems. This research represents a first step towards a computational theory of affect that can be leveraged to increase student motivation and learning. For example, bringing sensors to our children's schools addresses real problems of students' relationship to mathematics as they learn the subject and supports adaptive feedback based on an individual student's affective states. Within tutor environments, such sensors and animated pedagogical agents have the potential to support students by engaging them through social interaction.

As an example of automatics affect recognition, we described wireless sensors to recognize student emotion, along with a user model framework that predicted emotional self-concept. The framework was used in classrooms of up to 25 students with four sensors per student. By using stepwise regression we isolated key features for predicting user emotional responses to four categories of emotion. This was backed up by cross validation, and shows a small improvement using a very basic classier. This data has demonstrated that intelligent tutoring systems can provide adaptive feedback based on an individual student's affective state. As an example of automatic affect response, we described the evaluation of emotional embodied animated agents and their impact on student motivation and achievement.

There are a number of places for improvement in affective tutors. The effect of specific pedagogical actions on student learning should be investigated and perhaps used to quantitatively gauge the influence of competing tutorial strategies on learning. Additionally, summary information of all sensor values was used in the experiment described above. We may find better results by considering the time series of each of these sensors. In addition, the software in the Mental State Camera can be trained for new mental states or we might look at individual differences in the sensors. Creating a baseline for emotional detection before using the tutor system could help us to better interpret the sensor features.

Emotional predictions from sensors and agents are only a first step towards personalized feedback for students in classroom environments. We propose that tutors will ultimately identify desirable (e.g. flow) and non-desirable (e.g. boredom) student states. Different interventions will be tested in an attempt to keep students in desirable states as long as possible (e.g. a confused student might be invited to slow down, reread the problem and ask for a hint). Part of this approach includes embedding user models into tutors to provide instructional recommendations. Interventions algorithms are being developed based on tutor predictions, e.g. mirror student emotion, support student effort, provide more immediate feedback on student progress, and allow students increased control of their experience.

Modeling gender and student achievement level are potentially powerful as they can enrich the predictive power of the student model and improve teaching power at a very low cost. The importance of including gender and achievement level in a user model is not a mere hypothesis, but is based on extensive research, for examples on gender differences and learning at the K-12 level (Sax 2005; Beal 1994) Some research suggests that girls and boys have different approaches to problem solving (Fenneman et al. 1998; Carr and Jessup 1997) and even that they should be taught differently (Sax 2005). While this literature involves gender differences in the classroom, we have found empirical evidence over the years that gender differences exist when males and females use tutoring systems at the K-12 level (Arroyo and Woolf 2005).

Research on affective tutors may ultimately lead to delicate recommendations about the type of support to provide for individual students. Should male students receive affective support at all? Should all females be provided with learning companions? Should students with learning disabilities use learning companions? These are harder questions to answer from these experimental results. While our results suggest that high school females will affectively benefit more than high school males when exposed to learning companions, we cannot conclude that males in general should not receive affective learning companions. We might suggest that low achieving students (males and females) will highly benefit from affective learning companions. It was only high achieving males who clearly did not benefit from affective learning companions, though our data set is not large enough to provide statistically significant results on the impact of learning companions for a combination of math ability and gender characteristics of students. Further studies with larger number of students might result in more nuanced recommendations about how to modulate the feedback to individualize instruction in affective tutors.

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