# Affectively Intelligent User Interfaces for Enhanced E-Learning Applications

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**Abstract.** In this article we describe a new approach for electronic learning applications to interact with their users. First we discuss our motivation to build affectively intelligent user interfaces that can recognize learning related emotions and adapt to these through user modeling. In the remainder of the paper we describe the experiment we designed to elicit learning related emotions from students in order collect their physiological signals while they are experiencing those emotions and to classify those physiological signals into emotional states with pattern recognition algorithms.

## 1 Introduction

In the recent years there has been an increasing attempt to develop computer systems and interfaces that recognize the affective states of their users, learn their preferences and personality, and adapt to these accordingly (Bianchi and Lisetti, 2002; Conati and Maclaren, 2009; D'Mello et al., 2008; Hudlicka and McNeese, 2002; Nasoz and Lisetti, 2007; Scheirer et al., 2002). Studies conducted in this direction started with the birth of a new field in Computer Science: Affective Computing (Picard, 1997).

The main motivation behind all this research is that the current theories of cognition suggest there is a strong correlation between affect and cognition (Bower, 1981; Colquitt et al,. 2000; Damasio, 1994; Derryberry and Tucker 1992; Ledoux, 1992) and people emote while they are interacting with computers (Reeves and Nass, 1996); therefore machine perception needs to be able to capture such phenomenon in order to enhance our interaction with computers.

Main focus of our research is to recognize the emotions that users experience while they are interacting with computers and develop Affectively Intelligent User Interfaces that can adapt to these emotions for optimal Human-Computer Interaction. Objectives of our research in general include

- Designing experiments to elicit emotions from participants; collecting and measuring their physiological signals; and recording their facial expressions;
- Analyzing measured physiological signals with pattern recognition and machine learning algorithms to find unique patterns of physiological signals for each emotion;
- Using these patterns to recognize users' emotions in real-time;

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- Creating affective models of users that take their emotional states, personality, and preferences into account;
- Develop affectively intelligent user interfaces that combine i) emotion recognition through physiology and ii) affective user modeling to give appropriate feedback to the user about their emotional state and interact with them accordingly.

## 2 Motivation

There are several possible applications where emotions play an important role and where it is desirable and necessary to develop affective interfaces with an intelligent agent that can recognize and adapt to users' emotional state in the current context.

One of these possible applications is *learning* since it is one of the cognitive processes that is affected by people's emotional states (Goleman, 1995). *Frustration*, for example, leads to a reduction in the ability to learn (Lewis and Williams, 1989). It can also lead to negative attitudes towards the training environment and reduce a person's belief in his or her ability to do well in the learning or the training task. As a result, frustration can hamper learning.

Rozell and Gardner's study (2000) pointed out that when people have negative attitudes towards computers, their self-efficacy toward using them decreases, which then reduces their chances of performing computer-related tasks (when compared to those with positive attitudes towards computers). This research also emphasized that individuals with more positive affect exert more effort on computer-related tasks.

Another emotion that influences learning is *anxiety*. In training situations, anxiety is presumed to interfere with the ability to focus cognitive attention on the task at hand because that attention is preoccupied with thoughts of past negative experiences with similar tasks, in similar situations (Martocchio, 1994; Warr and Bunce, 1995). It follows that learning may be impaired when trainees are experiencing high levels of anxiety during training. Indeed, with a sample of university employees in a microcomputer class, Martocchio (1994) found that anxiety was negatively related to scores on a multiple choice knowledge test at the end of training. In addition, individuals who had more positive expectations prior to training had significantly less anxiety than individuals who had negative expectations of training.

Anxiety also appears to influence reactions to training. For example, with a sample of British junior managers enrolled in a self-paced management course, Warr and Bunce (1995) found that task anxiety was positively related to difficulty reactions in training. Individuals who experienced high task anxiety perceived training to be more difficult than individuals who experienced low task anxiety. In this study, interpersonal and task anxiety were assessed prior to training. Task anxiety was significantly higher than interpersonal anxiety and only task anxiety was associated with difficulty reactions. Similarly, in their meta-analytic path analysis, Colquitt et al. (2000) reported that anxiety was negatively related to motivation to learn, pre-training self-efficacy, post-training self-efficacy, learning, and training performance.

In summary, the most consistent findings are that frustration and anxiety are negatively related to self-efficacy, motivation, learning, and training performance. In addition, social anxiety may influence training outcomes when trainees are taught new tasks as a team. Furthermore, facilitating a mastery orientation towards the task may help to reduce the anxiety (e.g., attitude change) experienced during training and allow trainees to focus their cognitions on the task at hand, resulting in better learning (Martocchio, 1994).

In traditional classroom environments students are educated by live human teachers. This setting allows maximum level of natural interaction between the students and the teachers. Students have the opportunity to ask questions in real-time when they need more clarification or more examples. Teachers, on the other hand, can actually tell when their students are anxious, confused, frustrated, or bored and adapt their interaction with the students or adjust the pace of their teaching accordingly to accommodate different students.

In conventional electronic learning (e-learning henceforth) applications however there is no mechanism to assess students' various emotional states that may negatively affect their learning experience. There are several e-learning applications that employ user modeling in order to cater to the specific needs of different students with varying degrees of existing knowledge, skill levels, goals, and motivation levels (Barket et al., 2002; Corbett et al, 2000; Millan and Perez-de-la Cruz, 2002; Selker, 1994). However learning is a cognitive process that can be affected by variety of factors and a very important factor that these e-learning applications do not include in their user models is the students' affective state.

The strong correlation between students' learning performance and some of the affective states they experience (such as frustration and anxiety) makes it necessary to develop a mechanism for e-learning applications to recognize their users' affective states and interact accordingly. The main objective of the research discussed in this paper is to create affectively intelligent computer systems that can recognize learning related emotions of students through physiology; learn their preferences and personality through user modeling; and interact with the students by adapting to those emotions and student-dependent factors.

Affectively intelligent user interfaces we aim to develop for e-learning applications will enhance presence and co-presence for students and trainees in the learning environment. For example when the system recognizes that the learner is anxious, in response, it might provide encouragement in order to reduce anxiety and allow the individual to focus more attention on the task. Similarly, when the system recognizes the learner as being frustrated or bored it might adjust the pace of the training accordingly so that the optimal level of arousal for learning is achieved. Finally, when the system recognizes that a person is confused it might clarify the information just presented. All these adaptation techniques will improve the learner's sense of being in a real classroom environment where a live instructor would typically recognize these same emotions and respond accordingly.

## 3 Research Methodology

Our research methodology is two-fold:

- Recognizing students' emotional states by measuring their physiological signals and analyzing them with pattern recognition algorithms; and
- Through user modeling adapting the e-learning interface to the negative emotion of the student by also considering other student-dependent factors such as motivation, personality, preferences, knowledge and skill levels.

Our current method of emotion recognition is through analyzing Autonomic Nervous System (ANS) arousal. Students' physiological signals such as heart rate/blood volume pressure, galvanic skin response, temperature, and respiration are measured with wearable computers and they are classified into their corresponding emotion classes via pattern recognition algorithms. This is our choice of emotion recognition method because although people might be able to control their facial expressions, their vocal intonation, or natural language; they have minimal control over their ANS arousal, which makes it a trustable mode of input.

### 3.1 Experiment Design

The first step in developing the affectively intelligent user interfaces for e-learning applications is building the mechanism and the algorithms that will recognize students' emotional states. For this purpose we designed an experiment that aims to find a mapping between students' physiological signals and the learning-related emotions that they experience. Non-invasive wearable computers are used to measure participants' physiological signals such as heart rate/blood volume pressure, galvanic skin response, temperature, and respiration; and pattern recognition algorithms are employed to classify these physiological signals into learning related emotions.

**Procedure.** Participants of this experiment are University of Nevada, Las Vegas (UNLV) students who have taken a specific course within the last year. For this experiment a user interface is developed to administer an electronic test, which is consisted of multiple choice problems from the topics of that course they have taken within the last year. The students are given this test and for incentive, they are told that they will be given compensation in the form of a check for every problem they solve correctly and prove their answer on paper.

With this study we aim to elicit frustration from the participants so that we can measure their physiological signals while they are experiencing this emotion. Students are told that they will be compensated for each problem only if they choose the correct answer for that problem and prove their answer on paper. In order to frustrate them, the list of possible answers for some questions won't include the correct answer; therefore even if the students solve the problem correctly they won't be able to find the answer in the choices listed, which will lead to frustration. In addition, the use interface that is administering the multiple choice questions is running a faulty algorithm and is programmed to be occasionally and randomly non-responsive, in order to frustrate students even further.

Before the study, each participant is given an informed consent form to read. After they complete reading the informed consent form, they are presented with the experiment set-up, shown the non-invasive wearable computer that will be used to collect physiological data and explained how it works, and are informed about the compensation process. Then, they are given the opportunity to ask any questions they might have regarding the study and the procedures.

If they agree to participate in this experiment, then:

- They are asked to sign the informed consent form;
- They are asked to fill out the pre-experiment questionnaire;
- They are asked to put on the wearable computer that will collect their physiological signals during the experiment;

- They are presented with the test that is consisted of several problems from the topics of the specific course they have taken within the last year. They are given a specific time limit to solve each problem. Students are told that those problems are multiple choice questions with one correct answer listed among the choices. They are also told that they are required to solve the problem and prove their answer on paper to be compensated for that problem;
- Students' facial expression are recorded during the experiment with a standard web camera for annotation purposes only;
- Once they complete the test, they are asked to fill out the post-experiment questionnaire;

After completing the experiment students are fully debriefed and thanked for their time and participation.

### 3.2 Placement of Electrodes for All Measures

Participants' physiological signals including heart rate/blood volume pressure, galvanic skin response, temperature, and respiration are measured with one of the two non-invasive wearable computers: BodyMedia SenseWear armband or ProComp Infiniti 8.

**BodyMedia SenseWear Armband:** BodyMedia SenseWear armband is a completely wireless armband that is placed around the upper arm and can measure galvanic skin response and skin temperature. It also works in compliance with Polar WearLink coded chest transmitter, which collects heart rate data and communicates with the armband wirelessly. The chest strap is placed around the chest. The participants are shown how to wear the chest strap and they are given their privacy so that they can put it on themselves.

**ProComp Infiniti 8:** ProComp Infiniti 8 is a biofeedback and neurofeedback system that has 8 protected pin sensor inputs with two channels sampled at 2048 samples per second and six channels sampled at 256 samples per second. The sensors are connected to device on one end and the participant on the other.

Heart Rate/Blood Volume Pressure Sensor:
It is placed against the palmar surface of a fingertip with an elastic strap (not tight so as to cut off blood blow) or a small length of adhesive tape. It is very movement sensitive; therefore it can also be placed to an ear lobe with double sided adhesive tape.

Skin Conductance (Galvanic Skin Response Sensor):
The skin conductance sensor has two short leads that extend from the circuit box. At the end of each lead is a sensor snap similar to those on the extender cables. Each sensor strap is fastened around a fingertip tightly enough so the sensor surface is in contact with the finger pad but not so tightly that it limits blood circulation. The electrodes face against the palmar surfaces of the fingertips.

Temperature Sensor:
The temperature sensor is a 0.125 inch bead thermistor that can detect the temperature of the tissue (skin) on which it is applied. It is placed on a finger pad and held lightly in place by a hook and loop fastener ring.

Respiration Sensor:
The respiration sensor is sensitive to stretch. It is strapped around the chest or abdomen and it converts the expansion and contraction of the rib cage or abdominal area, to a rise and fall of the signal. It can be placed on top of clothing as long as clothing is not too bulky.

### 3.3 Software Used in the Experiment

In this experiment each participant is given an electronic test, which is consisted of several multiple choice problems from a UNLV course that they have taken within the last year. Students are given a specific time limit for each problem and they are told that they will be compensated for every problem they answer correctly and prove their answers on paper. Students are presented with the problems and choose and submit their answers through a graphical user interface (Figure 1). They will also be asked to show all their work and prove their answers on paper and told that compensation cannot be awarded otherwise.

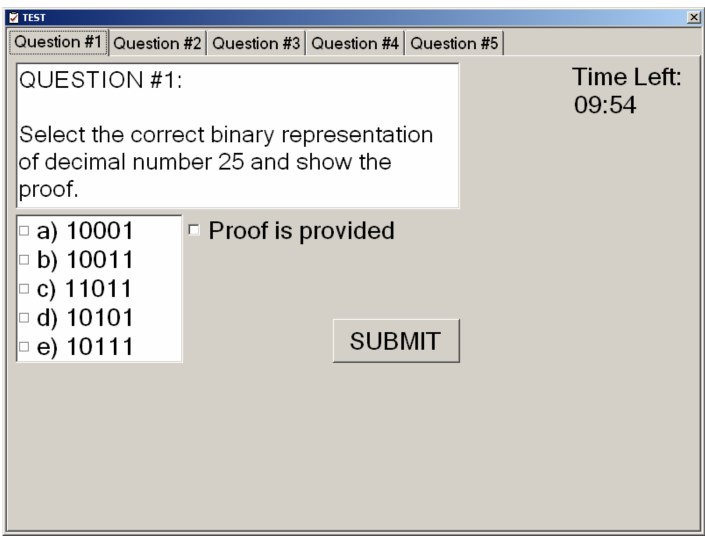


**Fig. 1.** Graphical User Interface Used to Administer the Electronic Test

In order to frustrate the students some of the problems do not have the correct answer among the list of provided answers. Also students are given limited amount of time for each problem. Once the time is up for a problem the system automatically displays the next problem and does not allow the student to go back to the previous one.

Remaining time for each question blinks on the interface to pressure the students and to frustrate them as the time passes. The interface will also has a faulty working algorithm, where sometimes the student needs to click several times (random number of times up to six) to select the desired choice. Students are subjected to similar difficulty while using the tabs to select a different problem and while clicking on the submit button to submit their answers, which are all designed to elicit further frustration from students.

### 3.4 Deception/Debriefing

In this study, misleading information is presented to the participants with the informed consent form in order to ensure the elicitation of frustration from them. This misleading information includes:

- Every multiple choice problem that will be presented to the participants has the correct answer listed among the list of possible answers;
- The software that is used to administer the test runs properly;
- Participants will be given compensation only for problems they solve correctly and prove their solution on paper.

Where in fact,

- For some problems in the test, the correct answer will not be listed among the list possible answers in order to deliberately frustrate the participants;
- The software that is used to administer the test has a faulty algorithm, which occasionally and randomly causes the interface be non-responsive;
- Participants will be given compensation for i) every question they submit an answer for and show/prove corresponding solution on paper and ii) all deceptive problems they attempt to solve.

For this experiment, misleading the participants is a necessary action in order to properly elicit the targeted learning related emotions. If the participants knew that the correct answers were not included in the list of choices for some of the problems or that the user interface is deliberately programmed to be non-responsive, not being able to find the correct answer or not being able use the interface efficiently would not frustrate them. Similarly, if they knew that they would be compensated for every problem they attempt to solve and submit an answer for, they would not try to solve the problems correctly, in turn would not get frustrated when they couldn't solve them.

Although misleading the participants makes this a deceptive research study, this deception does not expose the participants to more than minimal risk. The biggest expected effect of this deception is eliciting frustration from the participants, which is the desired outcome of this study.

In order to compensate for the deceptive nature of this study, at the end of the procedure the participants are fully debriefed with the correct information and they are given the opportunity to ask any questions they might have regarding this misleading information that was given to them. After their questions are answered they are also given the option to withdraw their participation and data from the study without affecting their compensation for the study. If they choose to do so, all data collected from that participant is destroyed immediately.

### 3.5 Emotion Recognition with Pattern Recognition Algorithms

We implemented pattern recognition and neural network algorithms, including k-nearest neighbor algorithm (Mitchell, 1997), discriminant function analysis (Nicol and Pexman, 1999), Levenberg-Marquardt backpropagation algorithm (Hagan and Menhaj, 1994), and resilient backpropagation algorithm (Riedmiller and Braun, 1993), to analyze the physiological data that is collected with the wearable computers while the participants are interacting with the system. The participants are observed while they are solving the questions in order to time stamp the points where they become frustrated because they cannot solve a particular question. The points where the faulty algorithm of the interface randomly becomes unresponsive are also time stamped.

After determining the time slots corresponding to the events in the experiment where the intended emotion was most likely to be experienced, physiological data corresponding to those time slots are determined. Features including minimum, maximum, average, median, and standard deviation are extracted from that data. Values for the extracted features of the physiological signals are then normalized and stores in a in a three-dimensional array. The three dimensions are the participant; the time stamped events during the experiment and extracted features. Extracted features are normalized using the following sample formula, which shows how average value of galvanic skin response is normalized:

$$normalized\_avg\_GSR = \frac{emo\_avg\_GSR - relax\_avg\_GSR}{relax\_avg\_GSR} \tag{1}$$

Normalized extracted features are then inputted to the pattern recognition algorithms as a 20-tuple (i.e. 4*5, where 4 is the number of types physiological signals, which are heart rate/blood volume pressure, galvanic skin response, skin temperature, and respiration; and 5 is the number extracted features, which are minimum, maximum, average, median, and standard deviation). We initially look at the collection of data samples in order to classify them into emotional states as opposed to analyzing each data signal individually. Further analysis will be performed to look at the effect of different emotional states on each physiological signal.

In this study, we try to differentiate both between emotions and between relaxed, non-aroused, non-emotional states versus tense, aroused, emotional states. Percentage of accuracy is expected to get lower when distinguishing between finer grained emotions.

### 3.6 User Modeling

Once the system recognizes the emotional states of students, it adapts to those states through students' user models that combine student dependent specifics such as knowledge, goals, and personality. User models in our affectively intelligent e-learning application are developed using Bayesian Belief Networks (BBN) (Pearl 1988). BBNs are our choice of user modeling approach due to the fact that unlike the traditional rule-based expert systems, BBNs are able to represent and reason with uncertain knowledge and they can update a belief in a particular case when new evidence is provided.

## 4 Conclusion

With the affectively intelligent learning interfaces we are developing, we aim to enhance presence and co-presence in learning environments by designing the system to recognize the students' affective states and adapt its interaction in order to aid their learning. For example once the system learns a student's skills, goals, personality, and preferences and recognizes her/his anxiousness during the interaction with the e-learning application, in response, it can provide their preferred style of encouragement, thus potentially reducing anxiety and allowing the them to focus more attention to the task at hand. Similarly, when the system recognizes that the learner is becoming frustrated or bored, it could adjust the pace of the training accordingly so that the optimal level of arousal for that student's learning is achieved. In this manner, the system will provide assistance to students in order to foster positive attitudes and emotions toward the e-learning application therefore will enhance their learning experience. All these adaptation techniques will improve the student's sense of being in a real classroom environment where a live instructor would typically recognize these same emotions and respond accordingly, thus enhancing presence.

## References


Barker, T., Jones, S., Britton, J., Messer, D.: The Use of a Cooperative Student Model of Learner Characteristics to Configure a Multimedia Application. User Modeling and User-Adapted Interaction 12, 207–224 (2002)

Bianchi, N., Lisetti, C.L.: Modeling Multimodal Expression of User's Affective Subjective Experience. User Modeling and User-Adapted Interaction 12(1), 49–84 (2002)

Bower, G.: Mood and Memory. American Psychologist 36(2), 129–148 (1981)

Colquitt, J.A., LePine, J.A., Noe, R.A.: Toward an integrative theory of training motivation: A meta-analytic path analysis of 20 years of research. Journal of Applied Psychology 85, 678–707 (2000)

Conati, C., Maclaren, H.: Empirically Building and Evaluating a Probabilistic Model of User Affect. User Modeling and User-Adapted Interaction (to appear, 2009)

Corbett, A., McLaughlin, M., Scarpinatto, S.C.: Modeling Student Knowledge: Cognitive Tutors in High School and College. User Modeling and User Adapted Interaction 10, 81–108 (2000)

Damasio, A.: Descartes' Error. Avon Books, New York (1994)

Derryberry, D., Tucker, D.: Neural Mechanisms of Emotion. Journal of Consulting and Clinical Psychology 60(3), 329–337 (1992)

D'Mello, S., Jackson, T., Craig, S., Morgan, B., Chipman, P., White, H., Person, N., Kort, B., el Kaliouby, R., Picard, R.W., Graesser, A.: AutoTutor Detects and Responds to Learners Affective and Cognitive States. In: Workshop on Emotional and Cognitive Issues at the International Conference of Intelligent Tutoring Systems, Montreal, Canada, June 23-27 (2008)

Goleman, D.: Emotional Intelligence. Bantam Books, New York (1995)

Hagan, M.T., Menhaj, M.B.: Training Feedforward Networks with the Marquardt Algorithm. IEEE Transactions on Neural Networks 5(6), 989–993 (1994)

Hudlicka, E., McNeese, M.D.: Assessment of User Affective and Belief States for Interface Adaptation: Application to an Air Force Pilot Task. User Modeling and User-Adapted Interaction 12, 1–47 (2002)

Ledoux, J.: Brain Mechanisms of Emotion and Emotional Learning. Current Opinion in Neurobiology (2), 191–197 (1992)

Lewis, V.E., Williams, R.N.: Mood-congruent vs. mood-state-dependent learning: Implications for a view of emotion. Special issue of the Journal of Social Behavior and Personality 4, 157–171 (1989)

Martocchio, J.J.: Effects of conceptions of ability on anxiety, self-efficacy, and learning in training. Journal of Applied Psychology 79, 819–825 (1994)

Millan, E., Perez-de-la Cruz, J.L.: A Bayesian Diagnostic Algorithm for Student Modeling and its Evaluation. User Modeling and User-Adapted Interaction 12, 281–330 (2002)

Mitchell, T.M.: Machine Learning. McGraw-Hill Companies Inc., New York (1997)

Nasoz, F., Lisetti, C.L.: Affective User Modeling for Adaptive Intelligent User Interfaces. In: Proceedings of 12th International Conference on Human-Computer Interaction, Beijing, China (July 2007)

Nicol, A., Pexman, P.M.: Presenting Your Findings: A Practical Guide for Creating Tables. American Physiological Association, Washington (1999)

Pearl, J.: Probabilistic Reasoning in Expert Systems: Networks of Plausible Inference. Morgan Kaufmann Publishers, Inc., San Francisco (1988)

Reeves, B., Nass, C.I.: The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places. Cambridge University Press, Cambridge (1996)

Picard, R.W.: Affective Computing. MIT Press, Cambridge (1997)

Riedmiller, M., Braun, H.: A direct adaptive method for faster backpropagation learning: The RPROP algorithm. In: Proceedings of the IEEE International Conference on Neural Networks, San Francisco, CA (1993)

Rozell, E.J., Gardner, W.L.: Cognitive, motivation, and affective processes associated with computer-related performance: A path analysis. Computers in Human Behavior 17, 199–222 (2000)

Scheirer, J., Fernandez, R., Klein, J., Picard, R.W.: Frustrating the User on Purpose: A Step Toward Building an Affective Computer. Interacting with Computers 14(2), 93–118 (2002)

Selker, T.: A Teaching Agent that Learns. Communications of the ACM 37(7), 92–99 (1994)

Warr, P., Bunce, D.: Trainee characteristics and the outcomes of open learning. Personnel Psychology 48, 347–475 (1995)