

Affect and learning: an exploratory look into the role of affect in learning with AutoTutor

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The role that affective states play in learning was investigated from the perspective of a constructivist learning framework. We observed six different affect states (frustration, boredom, flow, confusion, eureka and neutral) that potentially occur during the process of learning introductory computer literacy with AutoTutor, an intelligent tutoring system with tutorial dialogue in natural language. Observational analyses revealed significant relationships between learning and the affective states of boredom, flow and confusion. The positive correlation between confusion and learning is consistent with a model that assumes that cognitive disequilibrium is one precursor to deep learning. The findings that learning correlates negatively with boredom and positively with flow are consistent with predictions from Csikszentmihalyi's analysis of flow experiences.

Introduction

Scientific investigations of emotions fell out of fashion for most of the 20th century in the fields of experimental psychology, education and other social sciences, but there has been a renewed interest in emotions, moods and subtle affective states since the mid 1970s (Mandler, 1976, 1984, 1999; Ekman & Friesen, 1978; Picard, 1997; Rozin & Cohen, 2003a). Ekman and Friesen (1978) highlighted the expressive aspects of emotions with their Facial Action Coding System, which assumed that *basic* emotions could be identified by coding specific features and muscles of the face. These prototypical facial patterns were used to identify six basic emotions: happiness, sadness, surprise, disgust, anger and fear (Ekman & Friesen, 1978; Efenbein & Ambady, 2002). The coding system was tested primarily on static pictures rather than on changing expressions over time. Unfortunately for those researchers interested in the role of emotions in learning, it is doubtful whether these six emotions are either frequent or functionally significant in the learning process

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(Russell, 2003). More generally, some researchers have challenged the adequacy of basing a complete theory of emotions on these six emotions (Ellsworth, 2003; Hess, 2003; Rozin & Cohen, 2003a).

Our inquiry into the role of emotions in the learning process is not entirely devoid of theoretical guidance. Stein and Levine (1991), for example, have identified a link between a person's goals and emotions. Their model adopts a goal-directed, problem-solving approach. As with other theories of emotion that incorporate a hedonic principle, people prefer to be in some states (happiness) and prefer to avoid others (sadness). Their model assumes that people attempt to assimilate input into existing *schemas*, which are packages of world knowledge, such as stereotypes, scripts, frames and other categories of generic knowledge. Stein and Levine also assume that emotional experience is almost always associated with attending to and making sense out of incoming information. When the incoming information is novel, it causes a mismatch with existing schemas and results in arousal of the autonomic nervous system (ANS). When ANS arousal occurs in conjunction with a cognitive appraisal of the situation, an emotional reaction occurs. This theoretical model therefore predicts that learning almost always occurs during an emotional episode (Stein & Levine, 1991).

The model proposed by Kort *et al.* (2001a) also assumes that learning occurs in the presence of affective states. Kort *et al.* (2001b) have proposed a four quadrant *learning spiral* model in which emotions change while the learner moves through quadrants and up the spiral. The learning process is broken up by two axes, vertical and horizontal, labeled *learning* and *affect*, respectively. The learning axis ranges from 'constructive learning' at the top, where new information is being integrated into schemas, and 'un-learning' at the bottom, where misconceptions are identified and removed from schemas. The affect axis ranges from positive affect on the right to negative affect on the left. In this sense, Kort's model is similar to that proposed by Russell (2003).

From these two axes, Kort *et al.* (2001b) identify four quadrants. In quadrant I the learner is experiencing positive affect and constructing knowledge. At this point, the learner is working through the material with ease and has not experienced anything overly puzzling. Once discrepancies start to arise between the information and the learner's schemas, they move to quadrant II, which consists of constructive learning and negative affect. Here they experience affective states such as confusion. As the learner starts to discard their misconceptions about the material, they move into quadrant III. This is the quadrant of *unlearning* and negative affect, when the learner is experiencing states such as frustration. After the misconceptions are discarded, the learner moves into quadrant IV, marked by unlearning and positive affect. While in this quadrant the learner is still not sure exactly how to go forward. However, they do acquire new insights, search for new ideas and have a eureka (Ah hah!) experience when the insights are profound. Once they develop new ideas, they are propelled back into quadrant I. This would conclude one cycle around the learning spiral of Kort *et al.* As learners move up the spiral, cycle after cycle, they become more competent and acquire more domain knowledge (Kort *et al.*, 2001a,b).

Other researchers have proposed relations between learning and affect as well. In

his book *Emotional intelligence*, Goleman (1995) reported that expert teachers are able to recognize emotional states of their students and respond in ways that positively impact on learning. While Goleman does not describe precisely how this is accomplished, Csikszentmihalyi (1990) described an ideal learning state in which learners receive materials and challenges at just the right level of difficulty to become totally absorbed in the material. Time disappears; fatigue disappears. He called this absorbed state the *zone of flow*, the direct antithesis to boredom.

According to the constructivist theoretical frameworks, a person's affective states are expected to systematically influence how they process new material. The intrinsic motivation literature has identified affective states such as curiosity as indicators of motivation level and learning (Harter, 1981; Stipek, 1998). Learners with more intrinsic interest display greater levels of pleasure, more active involvement in tasks (Harter, 1992; Tobias, 1994), more task persistence (Miserandino, 1996), lower levels of boredom (Miserandino, 1996), less anxiety and less anger (Patrick *et al.*, 1993). Since a person's affective state is linked to their motivation level, intrinsically motivated learners who are affectively engaged should demonstrate more active involvement in tasks and more task persistence. A deeper understanding of the materials should be one important consequence (Jonassen *et al.*, 1999).

One class of cognitive models postulates an important role for *cognitive disequilibrium* in comprehension and learning processes (Piaget, 1952; Otero & Graesser, 2001; Graesser & Olde, 2003). Deep comprehension occurs when learners confront contradictions, anomalous events, obstacles to goals, salient contrasts, perturbations, surprises, equivalent alternatives and other stimuli or experiences that fail to match expectations (Mandler, 1976, 1999; Schank, 1986; Maturana & Varela, 1992; Jonassen *et al.*, 1999). Cognitive disequilibrium has a high likelihood of activating conscious, effortful cognitive deliberation, questions and inquiry that aim to restore cognitive equilibrium. The affective states of confusion and perhaps frustration are likely to occur during cognitive disequilibrium (Kort *et al.*, 2001a,b). Recent empirical research has indeed pointed to confusion as an important affective state for scientific study (Rozin & Cohen, 2003b). Confusion indicates an uncertainty about what to do next or how to act (Keltner & Shiota, 2003; Rozin & Cohen, 2003a). Thus confusion often accompanies cognitive disequilibrium. Similarly, states of perturbation and hesitation often indicate the need for clarification or more information (Smith *et al.*, 1974; Rozin & Cohen, 2003a).

The present study explored the role that affective states play in the learning process. College students learned about introductory computer literacy by interacting with an intelligent tutoring system (ITS) called AutoTutor (Graesser *et al.*, 1999, 2001, 2004). Auto Tutor helps students learn by holding a conversation with them in mixed initiative dialog. The ITS includes an animated conversational agent with synthesized speech, gestures and facial expressions that display emotions. AutoTutor facilitates learning with an effect size of 0.7σ compared with reading a textbook for an equivalent amount of time (Graesser *et al.*, 2001, 2004). The present exploratory study tracked the learners' emotions while they interacted with AutoTutor. These emotions were then correlated with learning outcome measures. It is possible that many affective states play an important role in learning. These include

frustration, confusion, boredom, flow and eureka, so these emotions were tracked during the course of learning. If constructivist theory and the claims about cognitive disequilibrium are correct, we should observe a positive relationship between confusion and learning gains (Kort *et al.*, 2001a,b; Graesser & Olde, 2003). According to the zone of flow theory, the state of flow should also show a positive correlation with learning (Csikszentmihalyi, 1990), while boredom should be negatively correlated with learning (Csikszentmihalyi, 1990; Miserandino, 1996). Similarly, a negative correlation is predicted between frustration and learning (Patrick *et al.*, 1993; Kort *et al.*, 2001a,b), whereas a eureka state should be positively correlated with learning.

Methods

Participants

The participants were 34 low domain knowledge college students drawn from the subject pool in the Department of Psychology at the University of Memphis. Students volunteered in order to obtain course credits. Another 20 participants were excluded from the study because of experimenter error or because they exceeded the subject matter domain criterion of 10 correct on a 24 item four-foil pre-test, i.e. their knowledge about computer literacy was not sufficiently low to satisfy our selection criterion. We selected low domain knowledge participants because these individuals were expected to obtain large learning gains and display a broad range of emotions.

Electronic materials

Participants interacted with AutoTutor on the topic of computer literacy, with a particular focus on questions about computer hardware. The questions were deeper questions (such as *why*, *how*, *what if*) that required a short paragraph of information to answer correctly. AutoTutor holds a mixed initiative dialog to assist the students in answering each question. The conversation typically takes 30–100 conversational turns to cover each of the 12 main questions. In addition to giving students short feedback on their contributions during each turn, AutoTutor gives hints, asserts missing information and corrects student misconceptions.

Affect coding system

The coding system consisted of one sheet of paper with a formatted table. The left column of the table was divided into 5 minute intervals that started at 0 (e.g. 0, 5, 10, etc.). The top row listed the affective states of interest for the study, along with a space to record the participant's state in the learning session (i.e. the subtopic and question being answered). The affective states were listed in the following order: frustration, boredom, flow/interest, confusion, eureka and neutral. The six states were functionally defined for the coders. Frustration was coded if participants seemed angry or agitated. Boredom was coded if participants seemed uninterested in the activity or responded slowly to the system and did not appear motivated. Flow

was coded when participants showed interest in the interaction or were paying attention and responding quickly. Confusion was coded if participants seemed puzzled and not sure how to continue or were struggling to understand the material. Eureka was coded if participants were observed to transfer from a state of confusion to a state of intense interest, as manifested by typing in answers very quickly after a period of inactivity. Neutral was coded if participants show a void of emotion and no facial features or if no emotions could be determined.

A total of five coders were used in this study. Only one coder observed each session. While it can be assumed that humans are experts at detecting emotion since we do it everyday, we are not always accurate (Ekman, 2003). All coders were given a training session lasting at least 30 minutes to ensure they understood and were comfortable with coding the affective states of interest. During the study they received random checks to ensure proper implementation of the coding system. Alternative methods to improve this coding system are described in the discussion section.

Knowledge tests

The test consisted of four alternative multiple choice questions on computer hardware. An example question is: 'What does the CPU use RAM for when a computer user executes programs? (a) long term storage, (b) to bypass the operating system, (c) short term storage, and (d) to hold the instructions necessary to reboot'. There were two versions of the test, with 24 items per version. These two tests were counterbalanced across participants to serve as either a pre-test of domain knowledge or a post-test to compute learning gains (i.e. post-test – pre-test). The two versions of the tests have produced equivalent means in past research (Craig *et al.*, 2004).

The 34 undergraduate participants were observed individually while they worked with AutoTutor. After an observation at the start of the learning session, an experimenter observed the interaction for 30 seconds every 5 minutes and recorded any noticeable affective state. In order to prevent biased reporting from the experimenters, they were given a list of six affective states to choose from, along with a short description of each. The raw observation data were converted into proportions for the purposes of analysis. Learning was operationally defined according to equation 1.

$$\text{Learning gain} = \frac{[(\text{proportion correct/post-test}) - (\text{proportion correct/pre-test})]}{[1 - (\text{proportion correct/pre-test})]} \quad (1)$$

Results

Equation 1 yielded a mean learning gain of $x = 0.31$ ($SD = 0.20$). Table 1 presents means, standard deviations and correlations for the six affective states and learning gains. The most prominent emotion was the flow state, followed by boredom and

Table 1. Means, standard deviations and correlations between affective states and learning gains (participants $n = 34$)

Measure	Mean	Standard deviation	Learning gains correlation
Boredom	0.18	0.20	-0.39 ^a
Confusion	0.07	0.11	0.33 ^a
Eureka	0.003	0.02	0.03
Flow	0.45	0.28	0.29 ^a
Frustration	0.03	0.09	-0.06

^a Significant correlations.

confusion. Frustration and eureka were extremely rare. Pearson correlations were computed between the observed affective states and the learning gain scores. As shown in Table 1, learning gains showed a significant negative correlation with boredom, but positive correlations with flow and confusion. The correlations between learning and the states of eureka and frustration were low and non-significant, which is not surprising since there was an obvious floor effect for these two affective states. When we computed correlations between affective states, all of the correlations were non-significant except for the negative correlation between flow and boredom, $r(32) = -0.68$, $P < 0.01$.

A multiple regression analysis was performed on the data to investigate which affective states were significant predictors of the observed learning gains. The results showed that the affective states predicted a significant 27% of the variance [$F(4,33) = 2.72$, $P < 0.05$]. When all emotions were entered into the regression analysis, the only one that reached significance was confusion [$t(32) = 2.30$, $P < 0.05$].

The data were coded for the presence or absence of the three correlated affective states and a $2 \times 2 \times 2$ ANOVA was performed on the learning gain scores. This analysis revealed only a main effect for confusion [$F(1,28) = 5.16$, $P < 0.05$]. Participants who exhibited confusion during the learning session outperformed those who did not. This resulted in a Cohen's effect size $d = 0.64$. Table 2 presents these data.

Table 2. Learning gain scores as a function of the presence or absence of three affect states

Affective state	Mean		Standard deviation		Cohen's d
	Present	Absent	Present	Absent	
Confusion	0.38	0.26	0.16	0.21	0.64
Flow	0.32	0.26	0.18	0.34	0.22
Boredom	0.28	0.35	0.21	0.18	-0.36

Discussion

The results of this study with AutoTutor provided evidence for a link between learning and the affective states of confusion, flow and boredom. Specifically, learning gains were positively correlated with confusion and flow, but negatively correlated with boredom. There was no significant correlation between learning gains and the states of frustration or eureka, because these two affective states had an extreme floor effect. For example, there was only one observation of eureka during the 20 hours of tutoring that were observed. This deficiency might be explained by our polling method, which made observations for 30 seconds every 5 minutes; we could have missed the rapidly experienced affective state of eureka.

The affective state of confusion appears to play an important role in the learning process. The effect size on learning (0.64) observed when confusion was present versus absent suggests that some level of confusion is critical for optimal learning. This result would be predicted by constructivism and the principle of cognitive disequilibrium (Mandler, 1984, 1999; Stein & Levine, 1991; Otero & Graesser, 2001; Graesser & Olde, 2003), as well as the model articulated by Kort *et al.* (2001a,b). Moreover, the fact that learning showed a positive correlation with flow but a negative correlation with boredom is compatible with the theoretical framework of Csikszentmihalyi (1990).

This study points to a link between affect and learning. However, there are still many questions left unanswered. Future research should attempt to pinpoint the exact places where emotion occurred during the learning process and see if they correspond with predicted learning patterns, such as that described in the Kort *et al.* (2001a,b) model. Future research could also implement a better observational design that allows identification of how reliable humans are at emotion detection.

While this study does not explain the full role of affect during learning, it does highlight the important role it can play in the learning process. We focused mainly on confusion. However, the roles of other affective states need further scientific investigation. An empirical understanding of the interplay between affect and learning will provide valuable insight into human learning processes.

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References

- Craig, S. D., Driscoll, D. & Gholson, B. (2004) Constructing knowledge from dialog in an intelligent tutoring system: interactive learning, vicarious learning, and pedagogical agents, *Journal of Educational Multimedia and Hypermedia*, 13, 163–183.
- Csikszentmihalyi, M. (1990) *Flow: the psychology of optimal experience* (New York, Harper Row).
- Ekman, P. (2003) *Emotions revealed: recognizing faces and feelings to improve communication and emotional life* (New York, Henry Holt and Co.).
- Ekman, P. & Friesen, W. V. (1978) *The facial action coding system: a technique for the measurement of facial movement* (Palo Alto, CA, Consulting Psychologists Press).
- Elfenbein, H. A. & Ambady, N. (2002) On the universality and cultural specificity of emotion recognition: a meta-analysis, *Psychological Bulletin*, 128, 203–235.

- Ellsworth, P. C. (2003) Confusing, concentration, and other emotions of interest: commentary on Rozin and Cohen (2003), *Emotion*, 3, 81–85.
- Goleman, D. (1995) *Emotional intelligence* (New York, Bantam Books).
- Graesser, A. C. & Olde, B. (2003) How does one know whether a person understands a device? The quality of the questions the person asks when the device breaks down, *Journal of Educational Psychology*, 95, 524–536.
- Graesser A., Wiemer-Hastings K., Wiemer-Hastings P., Kreuz, R. & The Tutoring Research Group (1999) AutoTutor: a simulation of a human tutor, *Journal of Cognitive Systems Research*, 1, 35–51.
- Graesser, A. C., Person N., Harter, D. & The Tutoring Research Group (2001) Teaching tactics and dialog in AutoTutor, *International Journal of Artificial Intelligence in Education*, 12, 257–279.
- Graesser, A. C., Lu S., Jackson, G. T., Mitchell H., Ventura M., Olney, A. & Louwerse, M. M. (2004) AutoTutor: a tutor with dialogue in natural language, *Behavior Research Methods, Instruments, & Computers*, 136, 180–192.
- Harter, S. (1981) A new self-report scale of intrinsic versus extrinsic orientation in the classroom: motivation and informational components, *Developmental Psychology*, 17, 300–312.
- Harter, S. (1992) The relationship between perceived competence, affect, and motivational orientation within the classroom: process and patterns of change, in: A. Boggiano & T. Pittman (Eds) *Achievement and motivation: a social-developmental perspective* (New York, Cambridge University Press), 77–114.
- Hess, U. (2003) Now you see it, now you don't: the confusing case of confusion as an emotion: commentary on Rozin and Cohen (2003), *Emotion*, 3, 76–80.
- Jonassen D., Peck, K. & Wilson B. (1999) *Learning with technology: a constructivist perspective* (Upper Saddle River NJ, Prentice Hall).
- Keltner, D. & Shiota, M. N. (2003) New displays and new emotions: a commentary on Rozin and Cohen (2003), *Emotion*, 3, 86–91.
- Kort B., Reilly, R. & Picard R. (2001a) An affective model of interplay between emotions and learning: reengineering educational pedagogy—building a learning companion, in: T. Okamoto, R. Hartley, Kinshuk & J. P. Klus (Eds) *Proceedings of the IEEE International Conference on Advanced Learning Technology: Issues, Achievements and Challenges* (Madison, WI, IEEE Computer Society), 43–48.
- Kort B., Reilly, R. & Picard, R. W. (2001b) External representation of learning process and domain knowledge: affective state as a determinate of its structure and function, in: *Proceedings of the Artificial Intelligence in Education Workshops* (San Antonio, TX, AIED), 64–69.
- Mandler, G. (1976) *Mind and emotion* (New York, Wiley).
- Mandler, G. (1984) *Mind and body: psychology of emotion and stress* (New York, Norton).
- Mandler, G. (1999) Emotion, in: B. M. Bly & D. E. Rumelhart (Eds) *Cognitive science. Handbook of perception and cognition* (2nd edn) (San Diego, CA, Academic Press), 367–384.
- Maturana, H. R. & Varela, A. (1992) *The tree of knowledge: the biological roots of human understanding* (Boston, Shambhala).
- Miserandino, M. (1996) Children who do well in school: individual differences in perceived competence and autonomy in above-average children, *Journal of Educational Psychology*, 88, 203–214.
- Otero, J. & Graesser, A. C. (2001) PREG: elements of a model of question asking, *Cognition & Instruction*, 19, 143–175.
- Piaget, J. (1952) *The origins of intelligence in children* (New York, International Universities Press).
- Picard, R. W. (1997) *Affective computing* (Cambridge, MA, MIT Press).
- Patrick B., Skinner, E. & Connell, J. (1993) What motivates children's behavior and emotion? Joint effects of perceived control and autonomy in the academic domain, *Journal of Personality and Social Psychology*, 65, 781–791.

- Rozin, P. & Cohen, A. B. (2003a) High frequency of facial expressions corresponding to confusion, concentration, and worry in an analysis of naturally occurring facial expressions of Americans, *Emotion*, 3, 68–75.
- Rozin, P. & Cohen, A. B. (2003b) Confusion infusions, suggestives, correctives, and other medicines, *Emotion*, 3, 92–96.
- Russell, J. A. (2003) Core affect and the psychological construction of emotion, *Psychological Review*, 110, 145–172.
- Schank, R. C. (1986) *Explanation patterns: understanding mechanically and creatively* (Hillsdale, NJ, Erlbaum).
- Smith, W. J., Chase, J. & Leiblich, A. K. (1974) Tongue showing: a facial display of humans and other primate species, *Semiotica*, 11, 201–246.
- Stein, N. L. & Levine, L. J. (1991) Making sense out of emotion, in: W. Kessen, A. Ortony & F. Kraik (Eds) *Memories, thoughts, and emotions: essays in honor of George Mandler* (Hillsdale, NJ, Erlbaum), 295–322.
- Stipek, D. (1998) *Motivation to learn: from theory to practice* (3rd edn) (Boston, MA, Allyn and Bacon).
- Tobias, S. (1994) Interest, prior knowledge, and learning, *Review of Educational Research*, 64, 37–54.