Monitoring Affective Trajectories during Complex Learning

Sidney D'Mello (sdmello@memphis.edu)
Department of Computer Science, University of Memphis
Memphis, TN 38152 USA

Roger S. Taylor (rstaylor@memphis.edu)
Institute for Intelligent Systems, University of Memphis
Memphis, TN 38152 USA

Art Graesser (a-graesser@memphis.edu)
Department of Psychology, University of Memphis
Memphis, TN 38152 USA

Abstract

This study investigated the transitions between affective states (i.e., boredom, flow, confusion, frustration, delight, and surprise) during learning while college students were tutored in computer literacy by AutoTutor, an automated tutoring system with natural language dialogue. Videos of participants' faces and the interaction histories were recorded and then played back for the participants to judge their own affective states. We developed a metric to measure the relative likelihood of transitioning from an affective state at time t_i to a subsequent affective state at time t_{i+1}. Several significant trajectories between affective states were identified. Instructional implications are discussed in the context of an expanded version of a cognitive disequilibrium model.

Keywords: Affective states; emotions; affect trajectories, affect sequencing; emotion dynamics; AutoTutor; learning; instruction.

Introduction

There is ample empirical evidence in the psychological literature that emotions (or affective states) are systematically influenced by the knowledge and goals of the learner, and vice versa (Mandler, 1984; Ortony, Clore, & Collins, 1988; Russell, 2003; Stein & Levine, 1991). As individuals interact in the social and physical world, they attempt to assimilate new information with existing knowledge schemas. When new or discrepant information is detected, a mismatch between input and knowledge occurs. Attention shifts to discrepant information, the autonomic nervous system increases in arousal, and the new information may modify the individual's goals and knowledge.

The learner experiences a variety of possible emotions, depending on the context, the amount of change, and whether important goals are blocked. However, this type of affective arousal that accompanies learning is still not well understood. For example, researchers have yet to narrow down the emotions that accompany deep level learning of conceptual material. The consequential impact of the emotions on knowledge acquisition and transfer is still not well understood.

A series of studies have recently explored the affective states that occur during complex learning. Studies by Graesser and his colleagues have collected online measures of affect, such as observations by trained judges and emote-aloud protocols, as well as offline judgments of emotions by multiple judges (Craig, et al., 2004; D'Mello et al., 2006; Graesser et al., 2006). These studies have revealed that the basic emotions identified by Ekman and Friesen (1978), namely anger, fear, sadness, joy, disgust, and surprise, typically do *not* play a significant role in learning (see also Kort Reilly, & Picard, 2001). Instead they documented a set of affective states that typically *do* play a significant role in learning, at least in the case of college students learning about computer literacy with an intelligent tutoring system. These affective states were boredom, flow (engagement, Csikszentmihalyi, 1990), confusion, and frustration. They also monitored the affective states of delight and surprise, which occurred less frequently. While some of these affective states might be viewed as purely cognitive in nature, our position is that they should be classified as affective states (or emotions) because these states are accompanied by significant changes in physiological arousal compared with a "neutral" state of no apparent emotion or feeling (Barrett, 2006; Meyer & Turner, in press; Stein & Hernandez, in press). Furthermore, affective-cognitive composites are particularly relevant to higher-order learning.

The aforementioned set of affective states can be situated within a broader perspective of emotion, in particular Russell's (2003) Core Affect framework. This perspective holds that an affective state is composed of two integrated components: *valence* (pleasure to displeasure) and *arousal* (activation to deactivation). These components can be depicted graphically with valence represented on the X-axis and arousal on the Y-axis. Moving from left to right along the X-axis (valence) would correspond to increasing feelings of pleasure. Moving upward along the Y-axis (arousal) would correspond to increasing feelings of activation and energy (see Figure 1).

The affective states of boredom, flow, confusion, and frustration will be the primary focus of this paper. These affective states have been previously correlated with learning

(Craig et al., 2004) and were found to occur more frequently than delight and surprise. These four affective states can be systematically mapped onto Russell's Core Affect framework. *Boredom* has a negative valence and low level of arousal. *Flow* has a positive valence and a moderate level of arousal. *Confusion* has a negative valence and a moderate level of arousal. Frustration has a high negative valence and a high level of arousal.

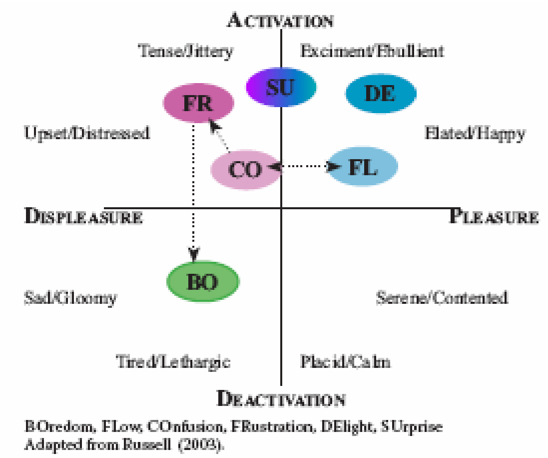

Figure 1 Russell's Core Affect Framework (Links denote transitions predicted to be greater than chance).

Students periodically change their affective states during the course of a learning session, so the transitions between these different affective states is a critical phenomenon to explore. The current investigation monitored and recorded the affective state transitions that individuals undergo while learning about computer literacy with the AutoTutor learning environment.

There currently is no widely accepted theoretical framework that explicitly addresses the issue of transitions between affective states during complex learning tasks. One cognitive model emphasizes the importance of *cognitive disequilibrium* (Graesser & Olde, 2003; Piaget, 1952) and can be extended to provide some predictions regarding likely affective state transitions. According to this theory, deep comprehension is most likely to occur 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 (Jonassen, Peck, & Wilson, 1999; Mandler, 1976; Schank, 1986). Individuals in a state of cognitive disequilibrium have a high likelihood of activating conscious and effortful cognitive deliberation, questions, and inquiry that are directed to restore cognitive equilibrium and result in learning gains. Kort, Reilly, and Picard (2001) predicted that the affective states of confusion, and perhaps frustration, are likely to occur during cognitive disequilibrium, while affective states such as boredom and flow would typically occur during cognitive equilibrium. This extended cognitive disequilibrium model would make a number of plausible predictions for the transitions between the states of boredom, confusion, flow, and frustration (see Figure 1 and Table 1).

Table 1. Predicted Affective Transitions

Affect at time t_i	**Affect at time t_{i+1}** Boredom	Flow	Confusion	Frustration
Boredom		-	-	?
Flow	-		+	-
Confusion	-	+		+
Frustration	+	-	?	

Note. (+) indicates expected transition
(-) indicates that the transition is highly unlikely
(?) indicates no explicit prediction from model

It is important to note the correlations between affective states and learning in order to fully understand some of the predictions in Table 1. Boredom is negatively correlated with learning, whereas confusion and flow are positively correlated with learning (Craig et al., 2004; Graesser at al., in review). Therefore, a bored learner is not expected to transition directly into flow or confusion. In contrast, transitions from confusion to flow and vice versa would be expected because of (a) there is a positive correlation between both of these emotions with learning and (b) an interplay between these affective states has been explicitly predicted by the cognitive disequilibrium model. Students in the state of flow are continuously being challenged within their zones of optimal learning (Metcalfe & Kornell, 2005) and experiencing two step-episodes alternating between confusion and insight. Transitions from confusion and flow to a state of disengagement (boredom) would also be highly unlikely. On the other hand, it is plausible that frustration may gradually transition into boredom, a crucial point at which the learner simply disengages from the learning process. Frustration is not likely to transition into flow in short learning sessions, whereas this may eventually occur over longer stretches of time. It should be noted that the model does not make predictions regarding likelihood of Boredom→Frustration or Frustration→ Confusion transitions. However, it is conceivable that these transitions might unfold if a learner is in a state of boredom or frustration for a long period of time.

Methods

Participants

The participants were 28 undergraduate students from a mid-south university who participated in this study for extra course credit.

Materials

AutoTutor. AutoTutor is a computer tutor that simulates human tutors and holds conversations with students in natural language (Graesser et al., 1999; 2005). AutoTutor helps students learn Newtonian physics and computer literacy by presenting challenging problems (or questions) from a curriculum script and engaging in a mixed-initiative dialog while the learner constructs an answer.

Procedure

The study was divided into two phases. The first phase was a standard pretest–intervention–posttest design. After completing the pretest, participants used the AutoTutor system for 32 minutes on one of three randomly assigned topics in computer literacy (Hardware, Internet, Operating Systems). During the tutoring session, a video of the participants' faces, their posture pressure patterns, and a video of their computer screen were recoded. Lastly, after completing the tutoring session, the participants completed a 36-item posttest assessment.

The second phase involved *affect judgments* by the learner, a peer, and two trained judges. A list of the affective states and definitions was provided for all judges. The states were boredom, flow, confusion, frustration, delight, and surprise. Judges were giving the option of making a *neutral* judgment to indicate a lack of distinguishable affect.

The affect judging session proceeded by displaying video streams of both the computer screen and the learner's face, both of which were captured during the AutoTutor session. The judges made judgments on what affective states were present at every 20-second interval (i.e., at the end of each interval the video automatically paused), as well as any other affective states they observed in between these intervals. Four sets of emotion judgments were made for each observed point. First, for the *self* judgments, the participant watched his or her own AutoTutor session immediately after the learning session. Second, for the *peer* judgments, participants came back a week later to watch and rate another participant's session on the same topic in computer literacy. Finally, two *trained* judges independently made judgments for the same sample of observations. However, the present study focused exclusively on the self-reported affect judgments.

Data Treatment

We are primarily concerned with transitions between affective states, so we ignored observations that were annotated as neutral. When aggregated across the 28 participants our results indicated that participants were primarily either bored (23%), confused (25%), or in a state of flow (28%). Frustration (16%) periodically occurred but delight (4%) and surprise (4%) were less frequent..

Scoring Procedure. We developed a scoring procedure to compute the transition likelihoods between affective states. Formally, this can be represented as L[C→X], where C is the current affective state at time t_i, X is the next state (t_{i+1}), and L is some likelihood function. For example consider a learner that only experiences two affective states: boredom and confusion. If we approximate the likelihood function with a conditional probability, then L[Confusion→Boredom] = Pr[Boredom|Confusion] can be interpreted as the probability of boredom following confusion while Pr[Confusion|Confusion] is the probability that a learner stays in the state of confusion.

Formally L[C→X] = Pr[X | C] = Pr[X ∩ C] / Pr[C]. Therefore, for each participant we simply counted the number of times emotion X followed C and divided this by the number of times emotion C was observed.

However, this method of computing the probability of affective transitions (i.e. Pr[X | C]) is prone to error due to its inability to account for the base rate of emotion X. For example consider a learner where Pr[Boredom|Confusion] = 0.4 and Pr [Confusion|Confusion] = 0.6. On the basis of the probabilities it is inappropriate to conclude that this learner when experiencing confusion is more likely to remain confused than transition into boredom, as indicated by the conditional probabilities. This is because the conditional probability does not factor in the base rate of the subsequent emotions. For example, suppose this learner experiences boredom 20% of the time and is confused for the remaining 80% of the tutoring session. In this case the prior probabilities (i.e. baserates) associated with boredom and confusion are Pr[Boredom] = 0.2 and Pr[Confusion] = 0.8. Therefore, even though Pr[Boredom|Confusion] < Pr[Confusion|Confusion] it is more likely for boredom to follow for a confused learner than remaining in confusion. This is because the probability of boredom following confusion is above and beyond the base rate of experiencing boredom (i.e., Pr[Boredom|Confusion] – Pr[Boredom] = 0.4 – 0.2 = 0.2). On the other hand, Pr[Confusion|Confusion] – Pr[Confusion] = 0.6 – 0.8 = -0.2, indicating that the learner is less likely to stay confused when the prior probability associated with experiencing confusion is factored into the equation.

In order to adjust for baserate, the likelihood of emotion X following emotion C was normalized by equation 1.

$$L[C \to X] = \frac{\frac{\Pr[X \cap C]}{\Pr[C]} - \Pr[X]}{1 - \Pr[X]} \qquad \text{(Equation 1)}$$

Our dividing the conditional probability above the base rate of emotion X (i.e. the numerator) by 1-Pr[X] normalized the scores to range between -∞ and 1. If L[C→X] = 1, we can conclude that emotion X always follows emotion C above and beyond the prior probability of experiencing emotion X. If, on the other hand, L[C→X] = 0, than X follows C at the chance level. Furthermore, if L[C→X] < 0, then the likelihood of emotion X following emotion C is much lower than the base rate of experiencing emotion X.

This metric to assess the probability of an emotion following another is equivalent to Cohen's kappa in computing agreement among raters (Cohen, 1960) (i.e., kappa = [p_{obs} - p_{exp}] / [1-p_{exp}], where p_{obs} and p_{exp} are observed and expected agreement respectively. From a probabilistic perspective equation 1 is consistent with computing Pr[X | C] when events X and C are temporally related, and contrasting this measure with the conditional probability when the events are independent. This is because if X and C are independent events then the conditional probability Pr[X | C] = Pr[X ∩ C] / Pr[C] = Pr[X] * Pr[C] / Pr[C] = Pr[X].

Results

The metric specified in Equation 1 was used to compute six data sets, one for each target emotion (boredom, flow, confusion, frustration, delight, and surprise). The metric permitted us to directly compare the relative likelihood that individuals in an affective state at time t_i, will remain in the same state or change to another affective state at time t_{i+1}. Repeated-measures ANOVAs, with the participant as the unit of analyses, were then computed to determine if there were significant differences between the current affective states (t_i) and the states that immediately followed (t_{i+1}).

Boredom

Figure 2a (on left) presents descriptive statistics (Means + 95% Confidence Interval, CI) for the likelihood that each of the 6 affective states immediately follows boredom. The ANOVA indicated that there were statistically significant differences among the likelihoods that the 6 affective states (including boredom) followed boredom, $F(5, 135) = 5.55$, $MSe = .05$, ($p < .05$ in this and all subsequent analyses unless explicitly specified). Tukey HSD Post-Hoc tests indicated that a learner experiencing boredom is more likely to stay bored ($M = .17$) than transitioning into confusion (.08), delight (-.03), flow (-.01), or surprise (-.02).

The results are compatible with the interpretation that a bored learner remains bored and transitions into frustration (.07) at rates significantly greater than chance. On the other hand Boredom→Confusion transitions are very rare; they are significantly less than what could be attributed to chance. Transitions into delight, surprise and flow, though low, are not statistically different from the base rate.

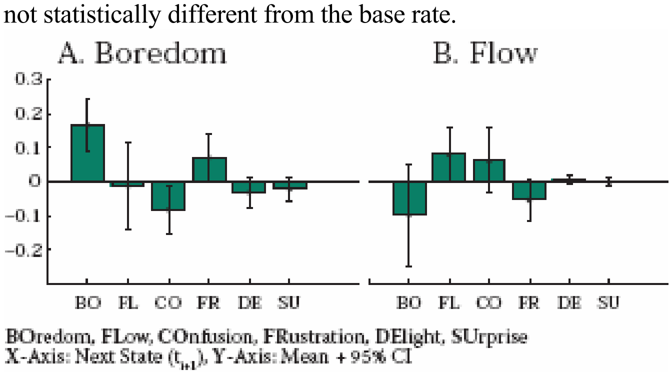

Figure 2 Current State (t_i): A: Boredom, B: Flow

Craig et al., (2004) reported that the affective state of boredom is negatively correlated with learning gains. There are noteworthy instructional implications of this finding and the current analysis of transitions. Given that learners who enter the affective state of boredom are likely to stay in that state, entering boredom may trigger a vicious cycle that prevents them from actively reengaging in the constructivist learning process. An additional discouraging finding is that bored learners are also significantly more likely to increase their level of arousal and make the transition to the state of frustration, which is also potentially detrimental to learning. Lastly, learners are unlikely to make the transition to the affective state of confusion. This may seem beneficial when based on the traditional negative connotations affiliated with confusion. However, this result is disappointing from another perspective: confusion has been shown to be positively correlated with learning (Craig et al., 2004; Graesser et al., in press).

Flow

A repeated measures ANOVA indicated that there were statistically significant differences in the likelihood that the 6 affective states (including flow) follow flow, $F(5, 135) = 2.20$, $MSe = .06$, $p < .05$, one-tailed test. Learners in the zone of flow are more likely to stay engaged ($M = .08$) or transition to confusion (.06, see Figure 2b). In contrast, they rarely experience frustration (-.06) or boredom (-.10). Transitions from flow to delight (-.01) and surprise (0) occurred at chance levels.

In contrast to the *vicious* cycle of the affective state of boredom (i.e., being stuck in an affective state negatively correlated with learning), learners in the affective state of flow are in a *virtuous* cycle in which they are likely to stay in the state of flow, which is positively correlated with gains in learning (Craig, et al., 2004). Furthermore, individuals in the state of flow are likely to transition to the state of confusion (also positively correlated with learning) and are unlikely to transition to the state of boredom (negatively correlated with learning) or frustration (presumably a negative emotion).

Confusion

An ANOVA showed statistically significant differences in the likelihood that the 6 affective states (including confusion) followed confusion, $F(5, 135) = 3.06$, $MSe = .06$. A confused learner is more likely to stay in confusion ($M = .09$) above and beyond the base rate in experiencing this emotion (see Figure 3a). Transitions from confusion to delight (0.0), flow (.02), frustration (.01), and surprise (.02) occur at chance levels. Confusion is rarely followed by boredom because the transition is significantly less than chance (-.17). Tukey HSD Post-Hoc tests confirm that confusion, flow, and surprise have a significantly higher likelihood of following confusion than does boredom.

Once again, confusion is sometimes viewed as an experience harmful to learning, but there is the alternative viewpoint that is compatible with cognitive disequilibrium. The latter model predicts that confusion could sometimes be *beneficial* to learning. Confusion may entice individuals to think more deeply about the topic, as reflected in the reported positive correlations with learning (Craig, et al., 2004; Graesser et al., in press). Another encouraging result was the finding that when learners are in the state of confusion, they are less likely to become disengaged and transition to the state of boredom, which is negatively associated with learning. It is also intriguing to note that confusion is sometimes followed by surprise. Perhaps this occurs when a learner identifies and discards a misconception, or fills a significant gap in understanding. Additional research is needed to explore these possibilities.

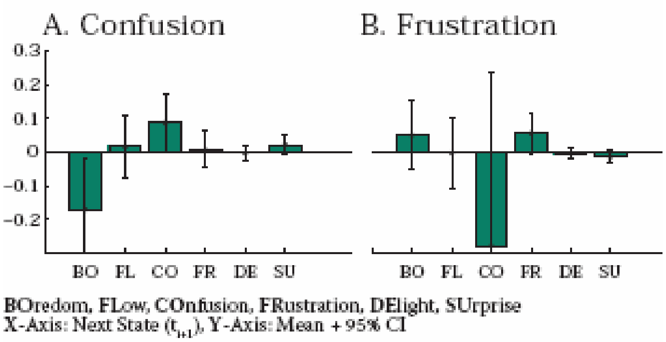

Figure 3 Current State (t_i): A: Confusion, B: Frustration

Frustration

An ANOVA showed no statistically significant differences in the likelihood that the 6 affective states follow frustration, $F(5, 135) = 1.17$, $MSe = .37$, ($p = .326$). However, the general pattern does indicate that frustrated learners are equally likely to remain frustrated ($M = .05$) or transition to boredom (.05) than experience flow (0.0) or confusion (-.28, see Figure 3b). This suggests that it might be very important for a tutor, either human or artificial, to alleviate frustration via empathy or with increased hints or prompts.

Delight

Our results suggest that learners experiencing delight are more likely to stay delighted ($M = .04$), transition into flow (.08), or be surprised (.04) then move into a state of frustration (-.10). We also find that transitions from delight to boredom (.05) and confusion (-.02) are statistically indistinguishable from the base rate in experiencing these emotions. These observations were confirmed by an ANOVA $F(5, 135) = 2.60$, $MSe = .04$.

While delight was a relatively rare affective state (4% in this study), the transitions from this state are encouraging. Learners are more likely to transition from delight to flow than to venture into frustration (Tukey HSD post hoc tests).

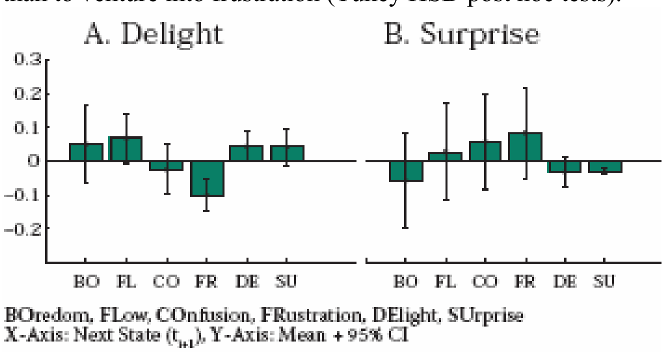

Figure 4 Current State (t_i): A: Delight, B: Surprise

Surprise

An ANOVA showed no statistically significant differences in the likelihood that the 6 affective states follow surprise, $F(5, 135) = .776$, $MSe = .12$, ($p = .568$).

Discussion

Earlier we made several predictions (see Table 1 and Figure 1) regarding the likelihood of certain emotion transitions on the basis of an extended version of the cognitive disequilibrium model and correlations between the affective states and learning gains. It appears that some of these predictions have been validated while others are in the right direction but not statistically significant. The supported predictions include the transitions from the state of boredom into confusion, flow into frustration, and confusion into boredom which occurred significantly *below* chance. The three predictions that had trends in the predicted direction, but were not statistically significant include the unlikely transition from flow into boredom and the likely transitions from flow to confusion and frustration to boredom. While this might be interpreted as evidence to support the extended cognitive disequilibrium model some of our findings question aspects of the model. In particular four predictions made by the model were not supported. However, it is important to note that in the current analyses we only considered 1-step transitions that occurred over an approximately 10-40 second period. It is reasonable to assume that some of the other transitions may require a broader time window to unfold.

There were also two interesting findings that were not addressed by the model. First, the transition from boredom into frustration occurred significantly *above* chance. Second, the transition from frustration into confusion occurred rarely, was not significant, and had a high degree of variability. This prompts speculation about how individual differences might be especially relevant to this transition. Perhaps some individuals disengage when frustrated, while others view the situation as a challenge and become more energized – and ultimately enter the confusion state while trying to resolve the current misunderstanding.

This research is one of the first endeavors to systematically investigate the manner by which learners dynamically experience affective transitions during complex learning. We acknowledge, however, that this research is preliminary and does not offer a complete explanation of the factors that “trigger” or promote certain affective transitions or inhibit others. The next step in this research will analyze relations between emotional transitions and personality traits, prior knowledge, pedagogical strategies of tutors, and social properties of animated conversational agents.

We are also currently investigating interactions between prior knowledge, learning gains, and affective transitions. However, of particular interest is the manner in which the context of the instruction influences particular affective trajectories. For example, we would like to determine the extent to which contextual factors such as the topic, the question, the number of attempts made by the student to answer the question, the tutor’s assessments of the students’ understanding and progress, and the feedback provided by the tutor to the students impacts the manner by which learners cycle through their emotions.

In addition to providing insights into the complex interplay between affective states and learning, the affective trajectories discovered in this research have facilitated a reconceptualization of the manner in which we have envisioned designing an emotionally-sensitive version of AutoTutor. Our original intentions were to use various unobtrusive measures (dialogue, facial expressions, body posture) to diagnose the affect of the learner, and then to modify AutoTutor's pedagogical strategies to systematically and quickly *react* to a learner's affective and cognitive states (D'Mello et al., 2005). However, it appears that learners experiencing negative affective states, such as boredom and frustration, are more likely to wallow in these states rather than transition into positive states of flow, delight, or even confusion. This suggests that a quick reactive policy of simply attempting to foster transitions from these negative states to emotions that have been positively correlated with learning may not suffice. Instead, or in addition, there is wisdom in including predictive measures to determine the onset of these negative affective states coupled with *proactive* pedagogical strategies to circumvent the incidence of negative emotions.

Acknowledgments

We thank our research colleagues at the University of Memphis and MIT. This research was supported by the National Science Foundation (REC 0106965, ITR 0325428, REESE 0633918). Any opinions, findings and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of NSF.

References

Barrett, L. F. (2006). Emotions as natural kinds? Perspectives on Psychological Science, 1, 28-58

Cohen, J. (1960). A coefficient of agreement for nominal scales, *Educational and Psychological Measurement* 20: 37–46, 1960.

Craig, S., A. Graesser, J. Sullins, & B. Gholson. (2004). Affect and learning: An exploratory look into the role of affect in learning. *Journal of Educational Media* 29:241-250.

Csikszentmihalyi, M. (1990). Flow: The Psychology of Optimal Experience. Harper-Row: NY.

D'Mello, S. K., Craig, S. D., Sullins, J., & Graesser, A. C. (2006). Predicting affective states through an emote-aloud procedure from AutoTutor's mixed-initiative dialogue. *International Journal of Artificial Intelligence in Education, 16*, 3-28.

Ekman, P, & W. V. Friesen. (1978). *The facial action coding system: A technique for the measurement of facial movement*. Palo Alto: Consulting Psychologists Press.

Graesser, A.C., Wiemer-Hastings, K., Wiemer-Hastings, P., Kreuz, R., & the TRG (1999). AutoTutor: A simulation of a human tutor. *Journal of Cognitive Systems Research, 1*, 35-51.

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.C., P. Chipman, B. C. Haynes, and A. Olney. (2005). AutoTutor: An intelligent tutoring system with mixed-initiative dialogue. *IEEE Transactions in Education* 48: 612-618.

Graesser, A.C., McDaniel, B., Chipman, P., Witherspoon, A., D'Mello, S., & Gholson, B. (2006). Detection of emotions during learning with AutoTutor. In R. Son (Ed.), *Proceedings of the 28th Annual Meetings of the Cognitive Science Society* (pp. 285-290). Mahwah, NJ: Erlbaum.

Graesser, A.C., Chipman, P., King, B., McDaniel, B., & D'Mello, S. (in review). Emotions and Learning with AutoTutor.

Jonassen D., Peck, K. & Wilson B. (1999). *Learning with technology: A constructivist perspective*. Upper Saddle River, NJ: Prentice Hall.

Kort, B., Reilly, R., & Picard, R. (2001). 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 IEEE International Conference on Advanced Learning Technology: Issues, Achievements and Challenges* (pp. 43-48). Madison, Wisconsin: IEEE Computer Society.

Mandler, G. (1976). *Mind and emotion*. New York: Wiley.

Mandler, G. (1984). *Mind and body: Psychology of emotion and stress*. New York: Norton.

Metcalfe, J., & Kornell, N. (2005). A region or proximal of learning model of study time allocation. *Journal of Memory and Language, 52,* 463-477.

Meyer, D. K., & Turner, J. C. (in press). Reconceptualizing emotion and motivation to learn in classroom contexts. Educational Psychology Review.

Ortony, A., Clore, G. L., & Collins, A. (1988). *The cognitive structure of emotions*. New York: Cambridge University Press.

Piaget, J. (1952). *The origins of intelligence*. New York: International University Press.

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.

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* (pp. 295-322). Hillsdale, NJ: Erlbaum.

Stein, N. L., & Hernandez, M. W. (in press). Assessing understanding and appraisals during emotional experience: The development and use of the Narcoder. In J.A. Coan, J.J. Allen (Eds). Handbook of emotion elicitation and assessment. New York: Oxford University Press