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Affect, Meta-Affect, and Affect Regulation during Complex Learning

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Affect, Meta-Affect, and Affect Regulation during Learning

Though affect is usually relegated to the sidelines as a perennially present but low-impact mood state, when triggered by the right event, emotions quickly claim the spotlight in our theatre of consciousness. Anger and rage rapidly consume us when we perceive that we have been wronged, elation fills an uneventful day when a much anticipated grant is funded, and we are enveloped in sadness upon hearing of the death of a loved one. Anger, joy, fear, sadness, disgust, surprise, angst, contempt, envy, grief, pride, shame, and ecstasy, are some of the everyday feelings that are familiar to us all. It could be argued that such affect states interact with every thought, modulate every decision, and influence every action, from the mundane to the elaborate.

Given the pervasiveness of affect in our daily lives (Scherer, Wranik, Sangsue, Tran, & Scherer, 2004), what should not come as a surprise to most, is that learning at deeper levels of comprehension is essentially an affectively charged experience (Calvo & D'Mello, in press). During learning with educational technologies like multimedia, hypermedia, and intelligent tutoring systems, learners may experience frustration when they have to manage a multitude of topic-related hyperlinks, confusion when illustrative figures and graphs seem to contradict the corresponding text, anger when a knowledgeable pedagogical agent withholds helpful guidance, boredom when the environment lacks stimulation, and perhaps even hopelessness or despair when their efforts seem unlikely to help them reach their goals. This negative portrait of the emotional experiences that accompany learning has a complementary positive side. Learners experience curiosity when they encounter novel and unfamiliar topics, eureka moments when insights are unveiled and major discoveries made, delight when challenges are conquered, and flow states (Csikszentmihalyi, 1990) when they are so engaged in learning that time and fatigue disappear. In agent-based learning technologies, learners can even experience feelings of

companionship when the agent appears helpful and supportive, and gratitude when the agent provides scaffolding to help them resolve an impasse or get them out of a stuck state.

In general, emotion and cognition are inextricably bound in educational technologies that require learners to generate inferences, demonstrate causal reasoning, diagnose and solve problems, make conceptual comparisons, produce coherent explanations, and show application and transfer of acquired knowledge. Contemporary theories of emotion and cognition assume that cognitive processes such as memory encoding and retrieval, causal reasoning, deliberation, and goal appraisal are modulated and facilitated by affect (Bower, 1981; Mandler, 1999; Ortony, Clore, & Collins, 1988; Scherer, Schorr, & Johnstone, 2001; Stein & Levine, 1991). The inextricable link between affect and cognition is sufficiently compelling that some claim the scientific distinction between emotion and cognition is artificial, arbitrary, and of limited value (Lazarus, 2000).

Although the 20th century has been ripe with emotion theory along with models of emotion and cognition, research investigating the links between emotions and learning is much more recent. Some of the most exciting research has emerged from the interdisciplinary arena that spans psychology (Dweck, 2002; Stein & Levine, 1991), education (Meyer & Turner, 2006; Pekrun, Elliot, & Maier, 2006), computer science (Arroyo, et al., 2009; Conati & Maclaren, 2009), and neuroscience (Immordino-Yang & Damasio, 2007). Some of this research has focused on student emotions in classrooms, where a broad array of affective responses are elicited in a number of contexts. Research in the context of learning technologies has focused on in-depth analysis of a smaller set of emotions (boredom, flow, confusion, frustration, anxiety, curiosity, delight, and surprise) that arise during deep learning over short time spans of one to two hours (Baker, D'Mello, Rodrigo, & Graesser, 2010; Conati & Maclaren, 2009; Craig,

Graesser, Sullins, & Gholson, 2004; D'Mello, Craig, Sullins, & Graesser, 2006; Graesser, et al., 2006).

This chapter discusses such research by providing a synthesis of affect-learning connections that we and our collaborators have explored over the past few years. We also discuss meta-affect and affect regulation as two related and equally significant phenomena. *Meta-affect* pertains to 'thinking about affect' and using this information to guide thought and action. *Affect regulation*, a relatively new and exciting field of research (Gross, 2008), addresses how people regulate their emotions either before or after they occur. After discussing these phenomena, we describe novel learning technologies that aspire to promote engagement and learning by modeling and externally regulating learner affect. We conclude by reflecting on some of the key findings and propose some avenues for further research.

Affect during Learning

The affect-learning theories that have emerged highlight the contributions of academic risk taking, motivation, mood states, flow, goals, and cognitive disequilibrium. They also describe how affect can play a role in learners' metacognitive processes and self-regulation. This section provides a brief overview of some of these theories followed by a discussion of some empirical research aimed at testing their critical hypotheses.

Theories of Affect and Learning

The academic risk theory and intrinsic motivation literature address how individual differences in risk taking behavior and motivation influence learners' emotional states and behavior choices. The academic risk theory contrasts (a) adventuresome learners who want to be challenged with difficult tasks, take risks of failure, and manage negative emotions when they

occur, with (b) cautious learners who tackle easier tasks, take fewer risks, and minimize failure and its resulting negative emotions (Clifford, 1988).

The intrinsic motivation literature has identified affective states such as curiosity as indicators of motivation level and learning (Harter, 1992; Stipek, 1988). Intrinsically motivated learners derive pleasure from the task itself (e.g., enjoyment from problem solving), while learners with extrinsic motivation rely on external rewards (e.g., praise from a pedagogical agent after successfully solving the problem).

Whereas these theories address individual differences, mood theories and flow theory are concerned with how mood states impact emotions and performance. Mood theories highlight the role of baseline mood states (positive, negative, or neutral) in learning, particularly for creative problem solving. In particular, flexibility, creative thinking, and efficient decision-making in problem solving have been linked to experiences of positive affect (Isen, 2001), while negative affect has been associated with a more methodical approach to assessing the problem and finding the solution (Schwarz & Skurnik, 2003). According to flow theory, learners are in a state of flow (Csikszentmihalyi, 1990) when they are so deeply engaged in learning the material that time and fatigue disappear. The zone of flow occurs when the structure of the learning environment matches a learner's zone of proximal development (Brown, Ellery, & Campione, 1998), so that the learner is presented with just the right sort of materials, challenges, and problems to the point of being totally absorbed.

Goal theory and cognitive disequilibrium theory specify how particular events predict emotional reactions and are pitched at a finer temporal resolution than theories that highlight individual differences and mood states. Goal theory is consistent with contemporary appraisal theories (Scherer, et al., 2001), arguably the most widely accepted account of emotion. Appraisal

is a presumably unconscious (but can also be consciously mediated) process that produces emotions by evaluating an event along a number of dimensions such as novelty, urgency, ability to cope, consistency with goals, etc. Goal theories emphasise interruptions of goals as the key appraisal dimension (Stein & Levine, 1991). In particular, the arousal level (intense/weak) of an emotional episode is dependent upon how great the interruption is to the person's goal whereas the valence (positive/negative) depends on the person's evaluation of the interruption (Lazarus, 1991; Mandler, 1999). Hence, outcomes that achieve challenging goals result in positive emotions, whereas outcomes that jeopardize goal accomplishment result in negative emotions (Dweck, 2002; Stein & Levine, 1991).

The cognitive disequilibrium theory postulates an important role for impasses (VanLehn, Siler, Murray, Yamauchi, & Baggett, 2003) in comprehension and learning processes. Cognitive disequilibrium is a state that occurs when learners face obstacles to goals, contradictions, incongruities, anomalies, uncertainty, and salient contrasts (Graesser, Lu, Olde, Cooper-Pye, & Whitten, 2005; Piaget, 1952). Cognitive equilibrium is restored after thought, reflection, problem solving, and other effortful deliberations. This theory states that the complex interplay between external events that trigger impasses, and the resultant cognitive disequilibrium, are the key to understanding the cognitive-affective processes that underlie deep learning. In particular, the affective states of confusion and perhaps frustration are likely to occur during cognitive disequilibrium because confusion indicates an uncertainty about what to do next or how to act.

Because emotions have the potential to impact motivation, attention, thoughts, and behavior, students should be equipped with strategies for regulating the emotions that arise during learning. However, theories of how emotional processes are regulated during learning with educational technologies have been slow to emerge. The cognitive-affective model of

learning (Moreno & Mayer, 2007) highlights the role of affect and motivation by suggesting that learners' emotions have the potential to direct energy and attentional resources to the learning task. The dual-processing model of emotion (Boekaerts, 2007) suggests that students' emotions can help direct the strategies they use during learning. For example, in the face of stress, some students may select non-productive strategies such as avoidance or distraction that redirect their attention away from their learning goals. Other students may see stress as an opportunity to improve and will tend to use coping strategies to help them deal with their emotions and stay focused on their learning goals. Although these theories underscore the importance of emotion on self-regulation during learning with educational technologies, many questions remain to be answered regarding the intricate relationship between emotion and self-regulation.

Identifying the Affective States that Occur during Complex Learning

The theoretical perspectives described above make a number of predictions about the affective experiences that arise during learning with educational technologies. We have tested some of these predictions in our analysis of emotion-learning connections in a variety of learning contexts, with a number of student populations, and with diverse methodologies. Table 1 presents an overview of 18 studies that we and our collaborators have conducted over the past six years.

The 'learning context' column in Table 1 refers to the educational technology used, and the educational task including computer tutoring, problem solving, text comprehension, and essay writing. The numbers in parentheses beside each learning context refer to the number of studies involving that context. As evident from Table 1, seven of the studies involved learning computer literacy with *AutoTutor* (Graesser, et al., 2004), an intelligent tutoring system with conversational dialogues (described in more detail in a subsequent section). Other computer

learning systems include *Aplusix* (Nicaud & Saidi, 1990), an ITS for mathematics, the *Incredible Machine* (Ryan, 2001), a simulation environment for logic puzzles, and a version of Operation ARIES!, a game-like ITS for critical thinking.

Emotions are notoriously difficult to measure because they are fuzzy, ill-defined, noisy, and compounded with individual differences in experience and expression. Methodological artifacts usually have an undesirable influence on the measured emotions, so it is imperative to obtain convergence across methodologies. This is precisely the approach we have adopted in our research, as illustrated by the diverse research protocols depicted in Table 1.

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The studies have yielded a number of insights into student affective experiences during deep learning and effortful problem solving with educational technologies. One finding is that confusion, frustration, boredom, and flow/engagement are the dominant affective states that student experience irrespective of the learning environment, the learning task, the student population, and the emotion measurement methodology. In contrast to these states that are consistently observed with high frequencies, some emotions are consistently observed, but with lower frequencies. Others are observed with relatively high frequencies, but only in some contexts. In particular, delight and surprise occur in many contexts, but the frequency of occurrence of these states is low. Curiosity occurs with high frequency, but it is only observed in some contexts; when students are intrinsically motivated with respect to the task, as was the case when aspiring law school students solved analytical reasoning problems from the LSAT. Similarly, anxiety is observed in high-stakes situations as was the case with the LSAT. Despite differences in patterns of occurrence, confusion, frustration, boredom, flow/engagement, delight,

surprise, curiosity, and anxiety are the major emotions that students experience during learning and problem solving; we refer to these as '*learning-centered*' states.

In contrast to the learning-centered emotions, the '*basic'* emotions consisting of anger, joy, surprise, disgust, happiness, and sadness (Ekman, 1992), are comparatively rare (one exception is happiness, which does occur in some contexts). These emotions are considered to be 'basic' by some who claim that they are innate, universally experienced and recognized, and cross cultural boundaries (Ekman, 1992; Izard, 1994), but others dispute this view (Barrett, 2006; Russell, Bachorowski, & Fernandez-Dols, 2003). Although these six basic emotions have claimed center-stage of most emotion research in the last four decades, our results suggest that they might not be relevant to lerning, at least for the short learning sessions of these studies. It is possible that they might be more relevant during learning in more extended time spans (such as completing a dissertation) or high stakes tests (e.g., final exams in courses). However, this hypothesis needs to be substantiated with some empirical evidence.

Relationship between Affect and Learning

In addition to specifying the emotions that are expected to occur during learning, the theories also predict specific relationships between emotions and learning gains. According to flow theory, the state of flow should also show a positive correlation with learning gains (Csikszentmihalyi, 1990), while boredom should be negatively correlated with learning gains. If constructivist theory and the claims about cognitive disequilibrium are correct, we should observe a positive relationship between confusion and learning gains if the learning environment productively helps the learners regulate their confusion. Similarly, a negative correlation is predicted between frustration and learning gains.

These predictions were tested by correlating the proportional occurrence of boredom, confusion, flow, and frustration with measures of deep learning collected in the studies with AutoTutor (see Table 1). Perhaps the most important and consistent finding was that confusion was positively correlated with learning gains (Craig, et al., 2004; D'Mello & Graesser, in press; Graesser, Chipman, King, McDaniel, & D'Mello, 2007). This relationship is consistent with the model discussed earlier that claims that cognitive disequilibrium is one precursor to deep learning (Graesser, et al., 2005) and with theories that highlight the merits of impasses during learning (VanLehn, et al., 2003). According to these models, confusion itself does not cause learning gains, but the cognitive activities that accompany confusion and impasse resolution are linked to learning, a finding that has received some empirical support (D'Mello & Graesser, in review).

One study confirmed the prediction that boredom was negatively correlated to learning while flow was positively correlated (Craig, et al., 2004). However, we have not been able to replicate this finding in subsequent studies. It might be the case that these states operate on longer time-scales, so their effects on learning could not be observed in short 30-35 minute learning sessions. Longer learning sessions would be required before the effects of these states can be observed.

One surprising finding was that frustration was not correlated with learning gains in any of the studies with AutoTutor. Frustration is a state that occurs when learners fail to resolve an impasse, they get stuck, and goals are blocked. The apparent lack of a relationship between frustration and learning might be attributed to the fact that the ITS used in these studies does not let a learner perseverate in a stuck state. Typical learning situations with educational technologies are fraught with such stuck states, since learners must often manage an abundance

of information with little direction or guidance (especially in multimedia and hypermedia contexts). In comparison, AutoTutor offers explanations and hints in order to advance the learning session. Withholding assertions and preventing a student from proceeding until they provide an appropriate response would presumably increase frustration and possibly impact learning.

There is some evidence to support this claim. For example negative affect (amalgamation of frustration, anxiety, and annoyance) was negatively correlated with posttests scores when the task was to read a passage in physics without any interference from a tutor (Linnenbrink & Pintrich, 2002). Frustration was also negatively linked to performance outcomes when students solved analytical reasoning problems in the absence of a tutor (D'Mello, et al., 2010) .

Meta-Affect during Learning

So far we identified the emotions that are relevant to learning with educational technologies, but the story does not end here. There is the question of how learners think about the emotions they experience. The *feelings-as-information* theory (Schwarz, in press) provides some useful insights into meta-affective processes (outside of learning contexts) that can be applied to learning with educational technologies. A central tenant of this theory is that affect has an informational function and different feelings (in context) convey different types of information. For example, a learner experiencing hopeless confusion while solving a physics problem might infer that there is a knowledge deficiency. Surprise, feelings of knowing (i.e., familiarity), and boredom are three states that inform learners about their knowledge levels (Ortony, et al., 1988).

Another principle of the theory is that the impact of a given feeling is proportional to its perceived information values with respect to the current situation. Feelings that are considered to

be directly related to the task provide more information than feelings considered to be purely incidental. For example, being sad because a pedagogical agent expressed disappointment in one's failure to comprehend a topic is relevant to the learning task and is of some value. However, sadness because it is a gloomy day is purely incidental to learning physics and is less informational in this context.

The final postulate of the theory is that when feelings are used as an information source, they are used as any other information source. Feelings can be used to modulate learning, help with decisions, and influence processing strategies. For example, experiencing confusion during problem solving might facilitate the deployment of analytical processing strategies (D'Mello & Graesser, in review; Schwarz, in press) that are focused on identifying and resolving the source of the confusion. Feeling that the learning goal has not been reached (i.e., the learner has not gained an understanding of the topic at hand) may lead to an increased use of learning strategies like summarizing or attempting to make inferences (Azevedo, 2009) or investing more time in learning the topic (Metcalfe, 2002)

Although the feeling-as-information theory postulates a significant role for meta-affect, confirmatory empirical data from learning contexts is sparse. We do know that learners' identify confusion, frustration, boredom, flow/engagement, delight and surprise when they are asked to emote-aloud (i.e., articulate their emotions) during learning or when they view videotapes of their tutoring sessions and judge their emotions at different points in time (D'Mello, et al., 2006; Graesser, et al., 2006). However, we do not know how reliably different classes of learners can identify these emotions. We suspect from 150 years of psychological research on emotions that some learners lack sensitivity to their own emotions, that other learners are hypersensitive, and that there is a large continuum of possibilities in between. We also know that people do not

always accurately identify the source of their feelings (Schwarz, in press), thereby limiting its informational values.

Research is conspicuously absent on how the learners perceive the causes, consequences, and information value of each affect state. The negative emotions are particularly in need of research. When a learner is frustrated from being stuck, the learner might attribute the frustration to either themselves ("I'm not at all good at physics"), the computer tutor ("The tutor doesn't understand this either"), or the materials ("There are too many hyperlinks here to even begin to synthesize"). As the theory suggests, the information value derived from the feeling of frustration would presumably depend on these attributions of cause (Weiner, 1986). When a student is confused, some students may view this as a positive event to stimulate thinking and attempt to show their ability by conquering the challenge; other students will attribute the confusion to their poor ability, an inadequate tutor, or poorly designed educational technology. When students are bored, they are likely to blame the tutor or material rather than themselves.

Affect Regulation during Learning

Once learners experience an emotion and are aware of the emotion, there is the question of how they might regulate the emotion. The goal of emotion regulation is presumably to downregulate negative emotions and upregulate positive emotions, although it is never quite this straightforward. For example, during collaborative online learning, one student might suppress happiness from receiving praise from a pedagogical agent when in the presence of a friend who has just received negative feedback from that agent. Regulation of emotions during learning with educational technologies is yet another area with considerably little empirical research. However, Gross (2008) has proposed an important process model of emotion regulation that is applicable

in everyday situations. Perhaps this model can yield some insights into how learners might regulate their affective states.

The model assumes that an emotion arises when an emotion-eliciting situation is experienced, attended to, and cognitively appraised (these different phases are a critical component of the model). The model proposes five broad emotion regulation strategies; four of these strategies can be deployed before the emotion (to be regulated) is experienced, while the onset of the emotion governs deployment of the fifth strategy. The first two strategies, situation selection and situation modification, are regulatory strategies aimed at selecting and modifying contexts (situations) that minimize or maximize the likelihood of experiencing certain emotions. For example, a learner who perceives that he or she has low computer skills may choose to use Wikipedia to gather information about a topic rather than using a more complex information source like PsychInfo in order to avoid the negative emotions (e.g., frustration in this case) associated with organizing a search, conducting a literature review, and synthesizing information. This is an example of situation selection, because the learner has opted out of a negative affect-induction situation (i.e., the complex information source).

Eventually, this learner may find that using a more complex information source is necessary in order to obtain the resources which are needed gain a full understanding of a given topic. If the learner has no choice in selecting the situation (i.e., the student has to use PsychInfo rather than Wikipedia), the learner can reduce his or her negative emotions by asking a peer or teacher to demonstrate the proper way use a complex search engine. Here, an emotion-inducing situation (i.e., using PsychInfo) has been alleviated by modifying the situation (i.e., seeking help from a peer or teacher).

Affect can also be regulated when a situation cannot be selected or modified. In these cases, a person can avoid attending to situational elements that might induce negative emotional reactions. For example, after receiving negative feedback from a pedagogical agent, a learner might try to keep frustration levels down by focusing on the instances where he or she received positive feedback, while ignoring negative feedback; this strategy is referred to as *distraction* (Gross, 2008). Alternately, *rumination* involves explicitly attending to the emotion-elicitation situation and can lead to a heightened intensity and increased duration of an emotional reaction (Bushman, 2002). Rumination would occur when a learner perseverates on the negative feedback, thereby increasing these negative emotions.

Affect can be regulated even when a person's attention is focused on an event that has the potential to elicit a particular emotional reaction. One such strategy is *cognitive reappraisal* (Dandoy & Goldstein, 1990), which involves changing the perceived meaning of a situation in order to alter its emotional content. For example, negative yet constructive feedback can actually be transformed into a more positive experience if the learner perceives the feedback in a different way. This would occur if the learner believes that the agent is only giving feedback in an attempt to help the learner resolve a misconception and understand the material more clearly. In essence, *cognitive reappraisal* occurs when the learner switches from a mindset of "the agent is trying to embarrass me" to "the agent just wants what's best for me".

Finally, *response modulation* is a strategy that can only be applied after the emotion is experienced. Perhaps the most widely studied form of response modulation is *expressive suppression*, which involves a sustained effort to minimize the expression of emotional behavior. Hence, a student in the throes of anger as a result of an agent's feedback can attempt to alleviate the anger by relaxing the body and taking slow deep breaths.

At this point in science, there is insufficient research documenting whether and to what extent students engage in these affect regulation strategies during learning with educational technologies. This leaves the door wide open for researchers to conduct more research in this area and propose models and theories that are more specific to educational technologies. For example, we recently conducted one preliminary study that tested the effect of cognitive reappraisal on alleviating boredom. Learners were asked to study 18 pages of the U.S. Constitution and Bill of Rights (this can be quite a dull read) from a web based digital text over a 30–60 minute session. Learners who were instructed to use a cognitive reappraisal strategy (experimental group) reported more arousal, valence, attentiveness, and demonstrated enhanced comprehension of the material than those in the control group, who were not instructed to reappraise their emotions (Strain & D'Mello, in press). Indeed, emotion regulation strategy training does have some benefits, at least within the context of this laboratory study. The pertinent question is whether this intervention is equally effective in more authentic learning contexts and with more advanced educational technologies.

Affect, Meta-Affect, and Affect Regulation with an Affective Tutor

After exploring the affective, meta-affective, and affect-regulatory processes during learning we turn our attention to an affect-sensitive version of an intelligent tutoring system (ITS) called AutoTutor. AutoTutor helps students learn topics in Newtonian physics, computer literacy, and critical thinking via a natural language conversational dialogue (Graesser, et al., 2004). AutoTutor's dialogues are organized around difficult questions and problems that require reasoning and explanations in the answers. AutoTutor actively monitors learners' knowledge states and engages them in a turn-based dialogue as they attempt to answer these questions. It adaptively manages the tutorial dialogue by providing feedback (e.g. "good job", "not quite"),

pumping the learner for more information (e.g. "What else"), giving hints (e.g. "What about X"), prompts (e.g. "X is a type of what "), identifying and correcting misconceptions, answering questions, and summarizing answers.

While the existing AutoTutor system is sensitive to learners' cognitive states, the affect-sensitive version is dynamically responsive to learners' affective states as well (D'Mello, et al., 2010). It detects and responds to boredom, confusion, and frustration because appropriate responses to these negative states could potentially have a positive impact on engagement and learning outcomes.

Design of the Affect-Sensitive AutoTutor

The affect-sensitive tutor embeds the learner and the tutor into an affective loop that involves *detecting* the learner's affective states, *responding* to the detected states, and *synthesizing* emotional expressions via animated pedagogical agents. The affect detection system monitors conversational cues, gross body language, and facial features to detect boredom, confusion, frustration, and neutral (no affect). Affect-detection accuracy is not perfect but is reasonably accurate (affect diagnosis is correct about 50% of the time compared to a 25% chance baseline).

Once the learner's affect has been detected, the tutor attempts to regulate the sensed affective state with an emotional statement. AutoTutor's strategies to respond to learner's emotions were derived from attribution theory (Weiner, 1986), cognitive disequilibrium during learning (Graesser, et al., 2005; Graesser & Olde, 2003; Piaget, 1952), politeness theory (Brown & Levinson, 1987; Wang, et al., 2008), and recent statements about the role of empathy is regulating negative emotions (Dweck, 2002; Lepper & Chabay, 1988). In addition to theoretical

considerations, the assistance of experts in tutoring was enlisted to help create the set of tutor responses.

The affect-sensitive responses attempt to regulate negative emotions by attribute the source of the learners' emotion to the material or the tutor instead of the learners themselves. So the affective AutoTutor might respond to mild boredom with "This stuff can be kind of dull sometimes, so I'm gonna try and help you get through it. Let's go". A response to confusion would include attributing the source of confusion to the material ("Some of this *material* can be confusing. Just keep going and I am sure you will get it") or the tutor itself ("I know I do not always convey things clearly. I am always happy to repeat myself if you need it. Try this one").

In addition to detecting and regulating learner affect, the affective tutor also synthesizes affect with facial expressions and emotionally modulated speech. These affective expressions include: approval, mild approval, disapproval, empathy, skepticism, mild enthusiasm, and high enthusiasm.

Evaluating the Affect-Sensitive AutoTutor

We have recently conducted an experiment that evaluated the pedagogical effectiveness of the affective AutoTutor when compared to the original tutor (D'Mello, et al., 2010). This original AutoTutor has a conventional set of fuzzy production rules that are sensitive to the cognitive states of the learner, but not to the learner's emotions. The obvious prediction is that learning gains should be superior for the affective AutoTutor.

The results of the experiment indicated that the affective AutoTutor was significantly more effective ($d = .713$) than the regular tutor for low-domain knowledge students, during the second half of the interaction. This suggests that it is inappropriate for the tutor to be supportive to these students before there has been enough context to show there are problems. Simply put, it

may not be wise to be supportive until the students need support. Second, the students with more knowledge never benefited from the affective AutoTutor. These students do not need the emotional support, but rather they need to concentrate on the content. Third, there are conditions when emotional support is detrimental, if not irritating to the learner. There appears to be a liability to quick support and empathy compared to no affect-sensitivity for students who have high domain knowledge and are being tutored early in the learning session. In summary, the evaluation of the affective AutoTutor has yielded some important insights, however, these findings are tentative and merit replication in a broader set of contexts.

Conclusions

This chapter has discussed the affective, meta-affective, and affect-regulatory processes that accompany deep learning and problem solving with educational technologies. We have identified a set of learning-centered affective states (confusion, frustration, boredom, flow/engagement, delight, surprise, anxiety, and curiosity) that were prominent in our analyses of affect during learning. Complimentary research validating this set of states with different learning environments, diverse student populations, and with alternate methodologies would represent an important advancement in this area. Of equal importance is the need for research studies that track emotions in the wild (i.e., in classrooms, school labs, and online courses) (Arroyo, et al., 2009; Baker, et al., 2010) and for extended periods of time. In particular, longitudinal studies that model how emotions emerge from interactions between affective traits, moods, and external events will represent a significant advancement in modeling the diffusive, elusive, fuzzy, and dynamic nature of emotions during learning.

Our discussions of meta-affect and affect regulation were unfortunately brief, mainly due to the paucity of research that has tracked these processes during learning sessions. This does not

come as a surprise, however, because with the exception of anxiety, systematic research into affect-learning connections is still in its infancy. In our view, identifying the emotions that are relevant to learning with educational technologies is the first step in such a research program. The next steps involve understanding the critical meta-affect and affect regulation processes that are active during learning. The time is ripe for exciting research along these fronts.

Finally, we described and evaluated an ITS that detects, regulates, and synthesizes affect. The idea of having a fully-automated affect-sensitive tutor was proposed only recently (Picard, 1997), so these affective tutors are indicators of the astonishing progress being made in this area. Although our initial experiment with the affect-sensitive AutoTutor yielded some positive effects, it should be noted that a one size fits all approach to affective feedback is not likely to adequately regulate all the emotional experiences that accompany learning. What is needed is a bold innovative approach that optimally coordinates cognition and emotions in a manner that is dynamically adaptive to the knowledge, goals, traits, moods, and styles of each individual learner. In addition to augmenting next-generation learners with cutting-edge technologies, such a research program will undoubtedly sustain significant discoveries bridging affect and learning for several decades.

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Table 1. Synopsis of Studies Investigating Affect during Learning with Educational Technologies

Learning Context	Domain	Population	Method	Reference
AutoTutor(7)	Computer literacy	College students	Observational, emote-aloud, cued-recall	(Craig, et al., 2004; D'Mello, et al., 2006; Graesser, et al., 2006)
Aplusix (1)	Algebra	High school	Observational	(Baker, et al., 2010)
Incredible Machine (1)	Logic puzzles	High school	Observational	(Baker, et al., 2010)
LSAT problem solving on computer (1)	Analytical reasoning	Aspiring lawyers	Cued-recall	(D'Mello, Lehman, & Person, in press)
Reading illustrated digital texts (2)	Mechanical reasoning	College students	Delayed self-report	(D'Mello & Graesser, in review)
Online course (1)	Statistics	College students	Online self-report, & cued-recall	
Operation ARIES! (3)	Critical thinking	College	Cued-recall	(Lehman, et al., in press)
Writing essays on computer interface (2)	Various topics	College	Cued-recall	