

Emotions in Advanced Learning Technologies

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Handbook of Emotions and Education, edited by R. Pekrun and L. Linnenbrink-Garcia,
Taylor and Francis Publishers.

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Keywords: Learning technologies, conversational agents, Intelligent Tutoring Systems

The research on was supported by the National Science Foundation (0325428, 633918, 0834847, 0918409, 1108845) and the Institute of Education Sciences (R305A080594, R305G020018). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of these funding sources.

Emotions in Advanced Learning Technologies

There is a vision that advanced learning technologies can optimize the delicate balance between emotions and the learning of academic material. Students are not prone to have much fun when they are expected to learn a dense array of new jargon, complex systems with many components, mental models with tradeoffs between variables, solutions to difficult problems, and other difficult academic content. The technology needs to be designed in some fashion that allows students to have emotionally satisfying experiences as they attempt to master material that is often viewed as tedious, pedantic, exceedingly challenging, or useless in their eyes. In an ideal world, the computer system would put the student in a zone of optimal concentration that targets relevant knowledge about the subject matter, at a pace that delivers the right challenges to the particular student at the right time.

A serious game could be engineered that brilliantly manages the tradeoff between fun and work. However, one would need to be very clever in designing such a serious game because young learners are skeptical of games that have any semblance of academic content. The game designer would need to smuggle in the academic subject matter under the students' attitudinal radar.

The goal of this chapter is to describe some advanced learning technologies that consider student emotions in addition to the conventional focus on cognition. The design of *affect-sensitive learning technologies* is likely to be quite complex because the designers of these systems need to have some understanding of cognition, emotions, motivation, pedagogy, aesthetics, communication, social interaction, sociology, and technology. Some design teams have reasonable intuitions on how to integrate these constraints into games, but most teams fail. The multibillion dollar game industry has not managed to market many games that incorporate

important academic content. Our hope is that the social sciences can provide a better understanding of the mechanisms that underlie affect-sensitive learning technologies.

There is a broad landscape of technology features that hold some promise in coordinating emotions and cognition as students learn difficult academic content. Below is a glimpse of some technological approaches that might hook the student into deeper learning:

- (1) Create a state of flow (or intense engagement) to the point where fatigue and time disappear. This may be accomplished by a simulation or game that delivers information, tasks, and scenarios at the student's zone of optimal challenge: not too easy or too difficult but just right.
- (2) Provide an engaging story narrative to sustain interest and coherence. The narrative would be integrated with the academic subject matter and promote its value.
- (3) Reward the student with points/resources that are extrinsically reinforcing or with experiences that are intrinsically reinforcing if the student is not already intrinsically interested in the topic.
- (4) Give the active student control over the interaction in order to allow autonomy and self-regulation.
- (5) Give the insecure student materials he/she can successfully master in order to build confidence and self-efficacy.
- (6) Interact with the student in a turn-by-turn conversation or collaboration to promote interactivity and social presence.
- (7) Give the student timely feedback on his/her actions so it is clear where the student stands in mastering the complex material.

- (8) Give feedback and guidance on the student's emotions so he/she can monitor the coordination between emotions and learning. A discouraged student may need an explanation that difficult material is sometimes confusing, frustrating, or boring.

This chapter examines how learning technologies can be coordinated with emotion mechanisms to facilitate the learning of difficult academic content. We concentrate primarily on difficult academic content because that is what students struggle with, avoid, or escape. The designers of some learning environments have intentionally considered the students' emotions when creating the artifacts, such affect-sensitive intelligent tutoring systems and serious games. This chapter focuses on those projects that collect empirical data on the learners' emotions, cognitive states, and learning, rather than untested learning environments. Sometimes emotions help and sometimes they interfere with learning so it is important to take stock of what we know about the emotions students experience and how these emotions are related to learning. The next section identifies moment-to-moment emotions that occur during complex learning, followed by a section on some theoretical frameworks to explain such emotions. The final section describes some advanced learning technologies that track, manipulate, and respond to student emotions with the goal of improving deep learning.

Our perspective on emotion is purposefully inclusive and broad in this chapter because there is not an abundance of research that has investigated moment-to-moment affective states during the learning of difficult material. We view "emotion" as an affective state or hybrid cognitive-affective state that deviates from a neutral affective state. A more nuanced classification of psychological states and dynamic processes will no doubt evolve as this research area matures. It is beyond the scope of this chapter to address enduring affective traits (e.g., curious, hostile), long-term moods (general anxiety), or motivational traits that span days, months, or years.

Emotions that Occur During Complex Learning

Contemporary psychological theories routinely assume that emotion and cognition are tightly integrated rather than loosely linked modules (Bower, 1992; Isen, 2008; Lazarus, 2000; Mandler, 1999; Ortony, Clore, & Collins, 1988; Pekrun, 2006; Scherer, Schorr, & Johnstone, 2001), but the focus has never been on moment-to-moment emotions during complex learning. This section documents what we know about the moment-to-moment emotions that students experience while interacting with advanced learning technologies that target complex material. The targeted learning environments require deep comprehension, reasoning, problem solving, and learning (hereafter called deep learning) in addition to the mastery and memory of simple facts, rules, and procedures (called shallow learning). Deep learning involves inferences, integration of information, conceptual elaboration of material through prior knowledge, reasoning strategies, problem solving heuristics, reflection, and other time-consuming, deliberate cognitive activities.

The active struggles of deep learning can be contrasted with the (typically) linear reading of textbooks in print or electronic media that are at low to intermediate levels of difficulty (Ainley, Hidi, & Berndorff, 2002; Reichle, Reineberg, & Schooler, 2010). For example, Ainley et al. (2002) collected reading times during the course of reading interesting versus uninteresting passages presented on the computer, followed by an assessment of comprehension. Their model predicted, and data confirmed, that topic interest and the associated curiosity from a title triggered positive affect, which in turn predicted persistent engagement during reading, whereas persistence predicted learning from text. It is likely that these trends will also apply to deep learning, but our assumption is that the cognitive disequilibrium of deep learning will give rise to a broader array of emotions.

Some moment-to-moment emotions during learning are intuitively obvious. For example, highly motivated students have the persistence to complete the expected tasks and experience

positive emotions when the tasks are successfully accomplished. They experience curiosity when the topics interest them, eureka moments when there are deep insights and discoveries, delight when challenges are conquered, and flow when they are so engaged that time and fatigue disappear. However, sometimes there are counterintuitive trends. In route to these positive affective states, learners may experience a rough terrain of confusion, frustration, irritation, and other negative emotions as they confront various obstacles in comprehension, production, reasoning, and problem solving. The students with maladaptive motivation and little interest in the material experience much more negative emotions than positive emotions. They quickly become bored and disengage after encountering a small amount of obstacles and dense technical content. Those with adaptive motivation and interest may visit anger or even rage on the trajectory to deep mastery of the subject matter, such as those individuals who have written dissertations, books, or grant proposals.

How are moment-to-moment emotions measured?

Researchers have used a variety of methods to measure the moment-to-moment emotions that students experience in technology-based learning environments (for reviews see Calvo & D'Mello, 2010; Du Boulay et al., 2011; D'Mello, in press; D'Mello & Graesser, 2010, in press; D'Mello, Craig, & Graesser, 2009; Graesser & D'Mello, 2012; D'Mello, Picard, & Graesser, 2007; Picard, 2010; Woolf et al., 2009). The primary methods are summarized below.

(1) *Trained observers during learning.* Trained observers periodically classify or rate the learner's emotions during the learning session (Baker, D'Mello, Rodrigo, & Graesser, 2010; Craig, Graesser, Sullins, & Gholson, 2004). The judges may have a checklist with discrete categories (e.g., boredom, confusion, frustration, etc.) or rating scales for dimensions of emotions or categories. The observers are trained on detecting emotions before they make their judgments on the emotions that students display during the process of interacting with the technology.

(2) *Self-report ratings of affective states during learning.* The students are stopped periodically during the course of learning and give judgments on their current states of emotions. The judgments may be in the form of ratings on emotional dimensions, selections on an emotion checklist, or a mark on a 2-dimensional affect grid that crosses valence (negative versus positive) and arousal, following the circumplex model (Barrett, 2006; Russell, 2003). Self-reports concurrent with learning are perhaps the most typical methodology in the literature on emotions in technology-advanced learning environments (Arroyo et al., 2009; McQuiggan & Lester, 2009; Sabourin, Rowe, Mott, & Lester, 2011; Woolf et al., 2009)

(3) *Emote aloud protocols by learners during learning.* An *emote-aloud* procedure collects spoken verbal expressions of emotions while the students complete a task (Craig, D'Mello, Witherspoon, & Graesser, 2008). The emote aloud procedure is analogous to the traditional think aloud procedure (Ericsson & Simon, 1993) except that the students are instructed to articulate their emotions instead of the cognitive content that typically surfaces in think aloud protocols. Most students do not know what it means to express emotions, so they need some guidance on what the alternative emotions might be and how to label them (Craig et al., 2008). Therefore, emotions are listed and defined before they start the learning task.

(4) *Retrospective identification of emotions by learners, peers, trained judges and teachers.* The observational and emote-aloud studies collect emotion judgments concurrently during learning, whereas the retrospective identification approach collects judgments after the learning session is completed. Various channels of communication and interaction are recorded, including facial expressions, conversation, computer displays, and interactions between the student and computer. A systematic polling procedure is implemented to sample emotion judgments by the original learner, peers of learners, trained judges, and teachers (D'Mello & Graesser, 2010; D'Mello, Lehman, & Person, 2011; Graesser & D'Mello, 2012).

(5) *Noninvasive automated detection of emotions.* Noninvasive sensing methods do not attach sensing devices to the learner and do not disrupt the normal stream of learning by probing the students with questions about their emotions or learning. The computers detect emotions of the learner by analyzing different communication channels and their interactions (Calvo & D’Mello, 2010; D’Mello & Graesser, 2010; Picard, 1997, 2010). The common communication channels include facial expression (D’Mello & Graesser, 2010; Grafsgaard, Boyer, Phillips, & Lester, 2011; Kapoor, Burleson, & Picard, 2007), speech parameters (Litman & Forbes-Riley, 2006), body posture (D’Mello, Dale, & Graesser, 2012; D’Mello & Graesser, 2009), and language and discourse interaction (D’Mello, Craig, Witherspoon, McDaniel, & Graesser, 2008; D’Mello & Graesser, 2012-b). Accuracy of these automated detection methods is modest, ranging from slightly above random guessing to perfect detection.

(6) *Biological detection of emotions by recording events in the brain and physiology.* These methods include the recording of heart rate, movements of the muscles, galvanic skin response, and brain activity (e.g., EEG, fMRI) (Arroyo et al., 2009; Calvo & D’Mello, 2010; McQuiggan & Lester, 2009; Picard, 2010). Most of these methods are invasive in the sense that it is obvious to the students that they are being recorded by physical instruments that have contact with their bodies. However, recent biological detection methods have become progressively less invasive, such wrist bands that record galvanic skin response (Poh, Swenson, & Picard, 2010) and the computation of heart rate from facial movements (Poh, McDuff, & Picard, 2010).

It is widely acknowledged that there is no gold standard for measuring what emotions the learners are actually experiencing during learning. None of these measures are perfect windows into emotional experience. The various measures correlate only modestly (kappas ranging from .2 to .5, see D’Mello & Graesser, 2010, with each measure having both virtues and liabilities. For example, the observational judgments (#1) have the virtue of tapping into the emotions as

they occur, but the liability of potential judge training biases and of inability to reexamine the events to refine the judgments. The self-report measures (#2 and #3) have the advantage of reflecting the phenomenology of the individual learner, but also come with the liabilities of disrupting or redirecting the learning process with probes, of sensitizing the learner to the experimenter's goals, and of learners having limited meta-knowledge of emotions. The retrospective judgments (#4) allow multiple judges to examine the events on multiple occasions, but again there are training biases and some of the extended context of the learning experience may get missed. The automated judgments (#5 and #6) have advantages of concurrent and systematic measurement, but the validity of the classification is often challenged, even when the reliability indices are comparable to humans. In light of these indeterminacies in measurement validity, researchers often collected multiple measures and adjust the confidence in their conclusions according to the consistency of the results.

What emotions occur during deep learning with advanced learning technologies?

There is a growing literature of research that tracks moment-to-moment emotions that occur when students interact with advanced learning environments, such as intelligent tutoring systems and serious games with agents (Arroyo et al., 2009; Baker, D'Mello, Rodrigo, & Graesser, 2010; Kapoor, Burselen & Picard, 2007; Calvo & D'Mello, 2010; Conati & Maclaren, 2010; D'Mello & Graesser, 2010, 2012-a, in press; Litman & Forbes-Riley, 2006; McQuiggan & Lester, 2009; McQuiggan, Robison, & Lester, 2010; Sabourin et al., 2011; Woolf et al., 2009). All of these studies have targeted difficult materials in STEM (Science, Technology, Engineering, and Mathematics) topics, such as physics, mathematics, biology, and computer science. The students have ranged from middle school to college students, primarily in sessions that last 1-2 hours. However, one limitation of these studies is that they have not spanned weeks or months, the normal time stretch for deep learning on STEM topics. They also have rarely been

integrated with the course curriculum, so there is no academic incentive for performing well on the learning tasks.

Most of studies that we have conducted have tracked the emotions that college students experience when they interact with AutoTutor on the topic of computer literacy (D’Mello & Graesser, 2010, 2012-a, in press; Graesser & D’Mello, in press). AutoTutor is an intelligent tutoring system (ITS) that helps students learn topics in Newtonian physics, computer literacy, and critical thinking through a mixed-initiative conversational dialog between the student and the tutor (Graesser, Jeon, & Dufty, 2008; Graesser, Lu et al., 2004; VanLehn et al., 2007).

AutoTutor’s dialogues are organized around difficult questions and problems (called main questions) that require reasoning and explanations in the answers. AutoTutor actively monitors the students’ knowledge states and engages them in a multi-turn conversational 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”), generating prompts to elicit specific words, correcting misconceptions, answering questions, and summarizing answers. The conversational moves of AutoTutor are guided by constructivist theories of pedagogy that scaffold students to actively generate answers, rather than merely instructing students with well-organized information delivery.

A small set of *learning-centered* emotions were found to dominate learning experiences with AutoTutor on the STEM topics in learning sessions of 1-2 hours. The primary emotions were confusion, engagement/flow, boredom, and frustration, with delight and surprise occasionally occurring but considerably less frequently. These learner-centered emotions are very different than the six “basic” emotions investigated by Ekman (1992) that are readily manifested in facial expressions: sadness, happiness, anger, fear, disgust, and surprise. They are

also different from the emotions that occur over longer stretches of time in academic, classroom, and social contexts, such as Pekrun's classification of academic emotions into epistemic, achievement, topic, and social emotions (which include anxiety, shame, pride, and other emotions tied to a student's self-concept)(Pekrun, 2006; Pekrun, Elliot, & Maier, 2006). One exciting direction for future research is to track the moment-to-moment emotions over longer intervals, which is entirely possible with current technologies that track emotions.

It is beyond the scope of this chapter to fully specify the conditions that trigger the different learner-centered emotions, but some major patterns are noteworthy (D'Mello & Graesser, 2010, 2012-a; Graesser & D'Mello, 2012, in press). One of the important positive emotions is what we will call engagement/flow, which is somewhere between the extremes of an enjoyable concentration on the material (engagement) and sustained focused attention to the point of flow, i.e., immersion and altered perception as time and fatigue disappear (Csikszentmihalyi, 1990). We make no attempt to sharply distinguish between mere engagement and intense flow, but we do assume that these are both positive affective states. The positive emotion of engagement/flow tends to occur when the learner is quickly generating information and receives positive feedback. The negative emotion of boredom tends to occur later in the tutoring session as the student fatigues and also when AutoTutor is disseminating information (asserting, summarizing, lecturing) as the student becomes overwhelmed with content. Frustration tends to occur when students are producing information they believe is on the mark, but they receive negative feedback because AutoTutor does not give the student due credit. Confusion tends to occur relatively early in the tutoring session when the discourse cohesion is low, the learner does not produce much information, the student is slow to respond, the feedback is negative or contradictory, and the student is not understanding AutoTutor's hints. These are moments when

the student is in thought and experiencing cognitive disequilibrium (see chapter in this volume by D’Mello & Graesser).

The research conducted by D’Mello and Graesser on AutoTutor revealed that three of these emotions have significant correlations with learning: confusion and engagement/flow have a positive correlation with learning, whereas boredom has a negative correlation (Craig et al., 2004; D’Mello & Graesser, in press; Graesser & D’Mello, in press). Frustration and the other emotions have no significant correlations with learning. Whether the emotions have a causal impact on learning is of course a separate question that will be addressed later in this chapter.

Do these conclusions about moment-to-moment emotions generalize to other advanced learning environments? Baker, D’Mello, Rodrigo, and Graesser (2010) tracked the emotions in three different computerized learning environments in order to assess the generality of our claims about the prevalence of learning-centered emotions. The first environment was AutoTutor, as we have already reported. The second involved students interacting with an intelligent tutoring system for mathematics, the *Aplusix II Algebra Learning Assistant* (Nicaud, Bouhineau, Mezerette, Andre, 2007). The third was *The Incredible Machine: Even More Contraptions* (Sierra Online Inc., 2001), a simulation environment in which students complete a series of logical puzzles. Together these three environments included different populations (Philippines versus USA, high school students versus college students), different methods (quantitative field observation versus retrospective self-report), and different types of learning environments (dialogue tutor, an ITS with problem-solving, and a problem-solving game). Baker et al. (2010) investigated the following affective states: confusion, frustration, boredom, engagement/flow, delight, surprise, and neutral. Learning gains or performance was also measured in some of these studies.

Baker et al. (2010) reported a number of conclusions about the relative prevalence of different emotions in the three environments. Boredom was frequent in all learning environments, was associated with poorer learning, and was associated with the dysfunctional behavior called *gaming the system*. Gaming the system consists of mechanically using system facilities to trick the system into providing answers rather than learning the domain knowledge. Frustration was considerably less frequent than boredom, engagement/flow, and confusion, was not associated with poorer learning, and was not an antecedent to gaming the system. Confusion was consistently observed in all learning environments, whereas there were informative differences in the occurrence of engagement/flow. Experiences of delight and surprise were rare. In essence, the distribution of emotions we found in AutoTutor was remarkably similar across the three learning environments, but there were some variations, as would be expected. Baker et al. (2010) also recommended that significant effort should be put into detecting and productively responding to boredom, frustration, and confusion. There should be a special emphasis on developing pedagogical interventions to disrupt the downward spiral of emotions which occur when a student becomes bored and remains bored for long periods of time to the point of frustration and eventual disengagement (D'Mello & Graesser, 2012-a, in press).

In another study conducted by D'Mello, Lehman, and Person (2011), students were tracked on emotions as they prepared for a law school entrance examination. The computer tracked them in a session where they solved difficult analytical reasoning problems from the law school admissions test (LSAT). Their facial expressions were recorded in addition to the computer screen. Students later completed a retrospective emotion judgment procedure. Students judged their emotions from the following alternatives: confusion, frustration, boredom, flow, contempt, curiosity, eureka, anxiety, anger, disgust, fear, happiness, sadness, surprise, and neutral. The results revealed that boredom, confusion, frustration, curiosity, and happiness (e.g.,

delight) were the major emotions that students experienced during problem solving, whereas anxiety was another important emotion. The emotion of anxiety is expected to surface more frequently when students anticipate evaluation and high stakes tests.

More recently, D'Mello (in press) performed a meta-analysis of 21 studies that used a mixture of methodologies to systematically monitor the emotions (15 emotions plus neutral). There were 1430 middle-school, high-school, college, and adult learners in five countries over the course of 1058 hours of continuous interactions, with a range of learning technologies including intelligent tutoring systems, serious games, and simulation environment. Engagement/flow, confusion, boredom, and frustration were the most frequent emotions and collectively comprised an astonishing 69% of all emotion reports. Indeed, we are quite confident that these are the critical learning-centered emotions that students experience during somewhat short (30 minutes to 2 hours) but in-depth learning sessions with technology.

Duration and sequences of emotions

Moment-to-moment emotions either reflect, mediate, moderate, or cause learning, so it is important to understand the emotion dynamics that accompany complex learning. The affective experiences that accompany learning are transient and dynamically change during learning rather than being persistent and static (unless the student becomes bored and disengages, as documented by Baker et al., 2010). Researchers have rarely investigated emotion dynamics during learning at a fine-grain level. However, the occurrence, duration, and sequencing of these emotions has been investigated in the AutoTutor system (D'Mello & Graesser, 2011, 2012-a) and occasionally some other technology-advanced learning environments (Baker et al., 2010; McQuiggan et al., 2010; Sabourin et al., 2011).

D'Mello and Graesser (2011) documented the duration of the learner-centered emotions while students interacted with AutoTutor on computer literacy. A precise temporal chronometry

would specify a point in time that an emotion is started, a duration from the start-point to the peak of the emotion, a duration of emotional experience around the peak, and a decay of the emotion until base level is achieved. The analyses modeled the decay rates of the emotions with exponentially decreasing functions. The decay rates showed the following trend for the six learner-centered emotions (Delight = Surprise) < (Frustration) < (Confusion = Boredom = Engagement/Flow). We would expect delight and surprise to be short-lived in most contexts, but the other four emotions should very much depend on the particular characteristics of the learning environment. Ideally we would want the system to lower the decay of engagement/flow and increase the decay of frustration and boredom. However, the status of confusion may be more complex. How long should a learner remain confused and thinking before the system generates an event to move the learner along?

Transitions from one emotion to another are undoubtedly influenced by the difficulty of the materials, the dialogue interaction between student and computer, the student's level of mastery, and a host of other factors. One way to test or discover the moment-to-moment transitions in emotions is to document the emotion transitions in a transition matrix and to identify the events in the learning environment that explain these transitions. These analyses have been conducted on the AutoTutor data sets (D'Mello & Graesser, 2012-a, in press) and the data collected in a serious game on biology called Crystal Island (McQuiggan et al., 2010; Sabourin et al., 2011).

The analysis of interest would compute the transition from one emotion to a different emotion, but in a manner that adjusts for base rates and the repetition of the same emotion. The repetition of the same emotion is of course important, and was captured in our previously reported analysis of emotion duration (D'Mello & Graesser, 2011). A statistical metric was devised to make the adjustments so that we could compute the likelihood of shifting from

emotion category at time t to another emotion category at time $t + 1$ in a way that quantitatively adjusts for the base rate likelihood of the emotion category at $t + 1$ and also the removal of a repeated emotion state.

Figure 1 summarizes the discoveries about emotion transitions. The transitions were aligned with a model of emotions that emphasizes the phenomenon of *cognitive disequilibrium* in learning. The significant transitions are identified in this section, whereas the next section turns to theoretical explanations. The chapter in this volume by D’Mello and Graesser discusses confusion and the cognitive disequilibrium theoretical framework in more detail. Learners start out experiencing either a neutral state or a state of engagement/flow, referred to as cognitive equilibrium. Eventually an obstacle or impasse is likely to occur, which triggers an emotion of confusion (and sometimes surprise, which is not depicted in Figure 1). The learner engages in effortful problem solving activities in order to resolve the impasse and restore equilibrium. Confusion transitions into frustration when the impasse cannot be resolved, the student gets stuck, and important goals are blocked. Our analysis of emotion transitions confirmed these paths depicted in Figure 1. That is, sequences of emotions during learning with AutoTutor were analyzed and tested with alternative transition models. A theoretical explanation of these transitions is provided in the next section.

Theoretical Frameworks

This section builds on the cognitive disequilibrium framework and other theoretical frameworks that attempt to account for the emotions that occur during learning with advanced learning environments. It is beyond the scope of this chapter, and indeed the current state of available research, to present a comprehensive theory of emotions during deep learning. Instead, we present an initial sketch that does justice to what we currently know and that will hopefully stimulate future research.

The previous section offered a cognitive disequilibrium framework to account for the durations and transitions between emotions during deep learning (See Figure 1). These emotion sequences capture the micro-level analysis of emotions and cognition, but fail to consider two theoretical components: moods (macro-level emotions) and traits of learners. This section augments the cognitive disequilibrium framework by pulling in moods and learner traits.

A cognitive disequilibrium theoretical perspective

The cognitive disequilibrium framework summarized in Figure 1 explains the moment-to-moment emotions during complex learning (see chapter by D'Mello & Graesser, this volume). Cognitive disequilibrium is a state that occurs when people face obstacles to goals, interruptions, contradictions, incongruities, anomalies, uncertainty, and salient contrasts (D'Mello & Graesser, 2012-a; Festinger, 1957; Graesser & D'Mello, 2011; Mandler, 1999; Piaget, 1952; Schwartz & Bransford, 1998). The handling of the cognitive disequilibrium depends on the learners' appraisal or reappraisal of their own abilities, their goals, the event that triggered the disequilibrium, and the context (Ortony et al., 1988; Scherer, et al., 2001; Strain & D'Mello, 2011). The learner is engaged and possibly in the zone of flow when the learning environment matches a student's zone of proximal development (Baumann, & Scheffer, 2010; Brown, Ellery, & Campione, 1998; Csikszentmihalyi, 1990). External events eventually create impasses, discrepancies, and the resulting cognitive disequilibrium, which in turn triggers confusion or surprise. When the cognitive disequilibrium and confusion persists, there is the risk of a downward spiral where the student becomes frustrated, eventually bored, and ultimately disengages from the task (Baker et al., 2010; D'Mello & Graesser, 2012-a; Sabourin et al., 2011). When the challenges of cognitive disequilibrium are conquered, then the student experiences the positive emotions of delight or engagement/flow (Csikszentmihalyi, 1990; D'Mello & Graesser, 2012-a, in press; Sabourin et al., 2011). There is an oscillation between cognitive disequilibrium

and the resolution of the disequilibrium when the learner experiences flow (Baumann & Scheffer, 2010). The parameters of this oscillation vary among students and learning environments. For example, some students enjoy high levels of disequilibrium, confusion, and frustration over a lengthy time span when playing games. Other students are not comfortable with the disequilibrium even in game environments.

Augmenting the cognitive disequilibrium framework with traits and moods

The learners' traits and moods would theoretically influence the occurrence, timing, and sequencing of the moment-to-moment emotions at the micro-level. Measures of enduring traits that are relevant to learning have tapped constructs of motivation, self-concept, and goal orientations (Daniels, et al., 2009; Frenzel, Pekrun, & Goetz, 2007; Linnenbrink, 2007; Pekrun, Elliot, & Maier, 2006; Schutz & Pekrun, 2007). The claims in this section are entirely theoretical, however, because investigation of micro-level emotions during learning is very much at its infancy. It is nevertheless important to briefly discuss how the cognitive disequilibrium framework would be expanded to incorporate traits and moods. The duration of the emotions and the likelihood of taking particular transitions depend on a host of factors, such as (a) the learner's interests, knowledge, self-concept, and traits, (b) the importance and difficulty of the subject matter in the learning environment, and (c) the mood that the learner starts out with prior to learning. Some examples are presented below.

(1) Consider students who are mastery-oriented rather than performance-oriented (Deci & Ryan, 2002; Pekrun et al., 2006), have high intrinsic motivation in the task rather than extrinsic, are risk takers rather than cautious (Clifford, 1988; Meyer & Turner, 2006), and/or have a high degree of conscientiousness or persistence (Miserandino, 1996). These students would be able to handle more time in states of confusion and frustration when encountering impasses, setbacks,

and negative feedback. In addition, they would be less prone to experiencing boredom and disengaging.

(2) Consider students with a self-concept that they have low aptitude and interest in mathematics so they do not believe that effort will help them master the material (Dweck, 2002; Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010). These students will quickly become bored and disengage when assigned mathematics problems. They may not have enough skills and knowledge of math to experience much confusion other than an initial bewilderment and quick escape.

(3) Consider a learning environment on a technical topic that is viewed by the students as being of little value and far above their heads. The students would attribute the challenge to a poor selection of materials and blame the instructional system, so they would quickly pursue the negative trajectory of frustration, boredom, and disengagement (Pekrun et al., 2010).

(4) Consider the positive versus negative moods that mediate or moderate the experience of moment-to-moment emotions and deep learning. Theories of affect and cognitive processing highlight the important role of baseline mood valences (positive, negative, or neutral) on learning. For example, flexibility, creative thinking, and timely decision-making in problem solving have been linked to experiences of positive affect (Clore & Huntsinger, 2007; Fredrickson & Branigan, 2005; Isen, 2008), whereas negative affect has been associated with a more methodical, focused, analytical approach to assessing the problem and finding the solution (Barth & Funke, 2010; Schwarz & Skurnik, 2003).

Manipulating and Responding to Emotions in Advanced Learning Technologies

This section describes some advanced learning technologies that were designed to track, manipulate or respond to learner emotions in an effort to promote deep learning. It is too early in this emerging research area to make firm conclusions on causal connections between emotions

and learning, but the studies described here have measured both moment-to-moment emotions and deep learning, with some directly testing causal relationships.

Emotion-Sensitive AutoTutor

An emotion-sensitive version of AutoTutor, called *Affective AutoTutor*, automatically detects student emotions based on multiple communication channels (D’Mello & Graesser, 2010; Graesser & D’Mello, in press). It responds to the students’ emotions by selecting appropriate discourse moves and displaying emotions through facial expressions and speech (D’Mello & Graesser, in press; D’Mello, Craig, Fike, & Graesser, 2009). The emotions of the students are automatically tracked by the features of their facial expressions, body posture, language, and discourse interaction. The primary student emotions that Affective AutoTutor tries to handle strategically are confusion, frustration, and boredom, because these are the emotions that run the risk of leading to disengagement from the task. The tutor continues business as usual when the student is emotionally neutral or in the state of engagement/flow. The emotions of delight and surprise are fleeting, so there is no need to respond to these states in any special way.

The cognitive disequilibrium framework predicts that confusion is a critical juncture in the learning process that is sensitive to individual differences. Some students may give up when experiencing confusion because they have a self-concept that they are not good at the subject matter, or when they are trying to avoid negative feedback. For these kinds of students, encouragement, hints, and prompts may be the best strategy for helping them get over the hurdle. Other students treat confusion as a challenge to conquer and expend cognitive effort to restore equilibrium; these students can be left to their own devices. An adaptive tutor would treat these students differently. An Affective AutoTutor would ideally discriminate these two students by the automated detection of confusion together with the quantity and quality of the student contributions in the tutorial interaction. When frustration is detected, the tutor agent would

express supportive empathetic comments to enhance motivation in addition to the usual hints or prompts to advance the student in constructing knowledge. It is important to minimize the likelihood of the student transitioning to boredom and disengagement in a downward trajectory, the Affective AutoTutor should respond to student boredom. When the student is bored, the tutor response would depend on the knowledge level of the student. Engaging material or challenging problems are appropriate for the more knowledgeable student, whereas easier problems are appropriate for the students with low subject matter knowledge so the student can build self-efficacy.

Affective AutoTutor has an emotion generator which enables the system to respond with suitable emotions. The agent speaks with intonation that is properly integrated with facial expressions that display emotions. The agent nods enthusiastically and expresses positive feedback language after the student has a correct contribution. The agent shakes its head in some versions or has a skeptical facial expression when the student contribution is low quality. There is an empathetic verbal message, kind facial expressions, and an encouraging demeanor when the student needs support. A small set of emotion displays like these examples went a long way in conveying the tutor's emotions.

A study was conducted to test the impact of different versions of Affective AutoTutor on learning gains (D'Mello, Craig, et al., 2009; D'Mello & Graesser, in press). The study compared the original AutoTutor without emotion tracking and emotional displays to an Affective AutoTutor version that is emotionally supportive. The *supportive* Affective AutoTutor had polite and encouraging positive feedback ("You're doing extremely well") or negative feedback after a low quality student contribution ("Not quite, but this is difficult for most students"). When the student expressed low quality contributions, the tutor attributed the problem to the difficulty of the materials to most students rather than blaming the student being tutored. There was also a *shake-up* version of

Affective AutoTutor. This version tried to shake up the emotions of the student by being playfully cheeky and telling the student what emotion the student is having (“I see that you are frustrated”). The simple substitution of this feedback dramatically changed AutoTutor’s personality.

The impact of the different AutoTutor versions on learning computer literacy depended on the phase of tutoring and the student’s level of mastery. The supportive emotion-sensitive AutoTutor had either no impact (for low knowledge students) or a negative impact (for high knowledge students) on learning during early phases of the tutoring session (i.e., within the first 30 minutes of the session). During a later phase of tutoring (i.e., the next 30 minutes), the supportive AutoTutor improved learning, but only for the low knowledge students. Low-domain knowledge students also performed better on a transfer test when they interacted with the supportive AutoTutor. An analysis of learners’ perceptions of both tutors indicated that their perceptions of how closely the computer tutors resembled human tutors increased over time, was related to the quality of tutor feedback, and was a powerful predictor of learning. Interestingly, the increase over time was greater for the Affective tutor over the control condition.

These results suggest that supportive emotional displays by AutoTutor may not be beneficial during the early phases of an interaction when the student and agent are “bonding” but that a supportive tutor is appropriate at later phases for students who have low knowledge and encounter difficulties. In essence, there may be an optimal *time for emoting* – just like there is in interactions between humans. The shake-up AutoTutor had more complex patterns of results that were never fully tested because an initial study indicated learning gains were the same as the original AutoTutor. However, most adults have a positive initial impression of the shake-up AutoTutor. Perhaps the playful shake-up tutor is motivating when boredom starts emerging for the more confident, high-knowledge learners, but this needs to be tested with more research in diverse student populations and learning environments.

Stimulating cognitive disequilibrium in Operation ARIES!

Earlier in the chapter we reported that learning gains were positively correlated with confusion as long as the learner was not persistently confused (Craig et al., 2004; D'Mello & Graesser, in press; see chapter in this volume). The question arises whether there is a causal relationship between confusion from cognitive disequilibrium and learning. Studies were conducted that manipulated cognitive equilibrium experimentally and measured the consequences on confusion and learning (D'Mello, Lehman, Pekrun, & Graesser, in press; Lehman, D'Mello, & Graesser, 2012; Lehman et al., 2011). This research is reported in the chapter by D'Mello and Graesser in this volume so this work is succinctly covered in this section.

This research was conducted in the context of *trialogs* very similar to those developed in a serious game called *Operation ARIES* (Millis et al., 2011) and a commercialized version called *Operation ARA* (Halpern et al., 2012). ARIES teaches scientific critical thinking in college students through a series of game modules, including those with two or more animated pedagogical agents. In the trialogs, a 3-way dialog conversation transpires among the human student, a tutor agent, and a student agent. The tutor-agent is an expert on scientific inquiry whereas the student-agent is a peer of the human student. A series of cases are presented to the student that describe experiments with possible flaws with respect to scientific methodology. For example, one case study described an experiment that tested a new pill that purportedly helps people lose weight, but there was no control group. The goal of the student and agents in the dialog is to identify the flaws and express them in natural language.

As reported in the D'Mello and Graesser chapter, studies were conducted that attempted to plant cognitive disequilibrium by manipulating whether or not the tutor agent and the student agent contradicted each other during the dialog. That is, the tutor agent and student agent

engaged in a short exchange about (a) whether there was a flaw in the study, and (b) the nature of the flaw if there *was* a flaw. The tutor agent expressed a correct assertion and the student agent agreed with the tutor in the *True-True* control condition. In the *True-False* condition, the tutor expressed a correct assertion but the student agent disagreed with an incorrect assertion. The *False-True* condition was the flip side with the tutor expressing a false assertion, whereas the *False-False* condition had both the tutor and the student agreeing on incorrect information.

The central question is whether the contradictions would plant confusion and subsequent reasoning at deeper levels, which in turn would improve learning (contradiction → confusion → deep reasoning → deep learning). In one measure of confusion, the agents asked the student questions after particular points of agent contradiction in the conversation. For example, the agents turned to the human and asked “Do you agree with Chris (student agent) that the control group in this study was flawed?” A signal of confusion would be reflected in answers that were either incorrect or uncertain. This confusion would allegedly stimulate thinking, reasoning and learning. The data indeed confirmed that the contradictions had an impact on the humans’ answers to these forced-choice questions immediately following a contradiction. The correct responding showed the following order: True-True > True-False > False-True > False-False conditions. These findings indicated that learners typically agreed with the agents when the agents agreed (True-True, False-False), but were often confused when there was a contradiction between the two agents (True-False or False-True). Interestingly, there was also some evidence that disequilibrium and/or confusion caused more learning at deeper levels of mastery, as reflected in a delayed test on scientific reasoning. Specifically, experimental conditions with agent contradictions often produced higher performance on multiple choice questions that tapped deep levels of comprehension compared with performance in the true-true condition, but only if learners were confused by the contradictions during training. Similarly, students who were

confused by the contradictions during training were more likely to correctly identify flaws in new case studies at a test phase. These results are consistent with the hypothesis that there may be a causal relationship between cognitive disequilibrium and deep learning, with confusion playing a moderating role on the effect of the contradictions on learning.

Similar to our studies with trialogs, Forbes-Riley and Litman (2011) have used an intelligent tutoring system called *UNC-ITSPOKE* to examine whether automatic responses to learner uncertainty could improve learning outcomes. Uncertainty is an affective state that is similar to confusion and plays an important role on the process and products of learning. *UNC-ITSPOKE* was designed to teach students about various physics topics, with the capability to automatically detect and respond to learners' correctness/incorrectness, and certainty/uncertainty. Forbes-Riley and Litman (2011) compared learning outcomes between learners who received adaptive responses to uncertainty (adaptive), random responses to uncertainty (random), or no responses (control). The adaptive condition achieved slightly (but not significantly) higher learning outcomes than the random and control conditions. Interestingly, the results suggested that it is not the presence or absence of adaptive responses to uncertainty, but *how many* adaptive responses were given. Learners who received a high frequency of adaptive responses to uncertainty achieved significantly higher learning outcomes than those who received a low frequency of adaptive responses. Forbes-Riley and Litman (2011) concluded that there is merit in offering adaptive feedback to uncertainty, and that such feedback can improve learning outcomes.

A serious game with narrative in Crystal Island

The links between emotions and learning are fundamental to the design of serious educational games that target complex academic topics (Conati, 2002; Forsyth et al., in press; McNamara, Jackson, & Graesser, 2010). Educational games ideally are capable of turning work into play by

minimizing boredom, optimizing engagement/flow, presenting challenges that reside within the optimal zone of confusion, preventing persistent frustration, and engineering delight and pleasant surprises (Lepper & Henderlong, 2000; Ritterfeld, Cody, & Vorderer, 2009). Although educational games increase learners' engagement, they may or may not provide instructional support that leads to improved learning (O'Neil & Perez, 2008; Tobias & Fletcher, 2011). Educators must balance a trade-off between game environments that are engaging but tangential to learning, and environments that promote deep learning but fail to foster engagement. An analysis of moment-to-moment emotions is presumably needed to better understand the trade-offs.

Lester and his colleagues have recently conducted studies that track emotions while middle school children learn about biology in a serious game called *Crystal Island* (McQuiggan, Robison, & Lester, 2010; Sabourin et al., 2011). This is an immersive educational game that capitalizes on the principle of narrativity, which allegedly (a) motivates learners to initiate and persist in game play, (b) increases study time on academic content, and (c) increases learning. In *Crystal Island*, learners attempt to identify the source of an infectious disease that is spreading among the members of a research team on *Crystal Island*. Students make gradual steps toward diagnosing the cause of the disease through the generation of questions, generation of hypotheses, collection of data, and analysis of data. The affective states were tracked during the learning experience by having students self-report every 7 minutes whether they are experiencing any of the following 7 states: anxious, bored, confused, curious, excited, focused (engaged), and frustrated. The researchers also tracked "off-task" behavior during the game that is manifested by irrelevant actions. The transitions between emotions were found to interact with the off-task versus on-task behaviors along interesting trajectories. For example, students who remained on-task after reporting confusion tended to be focused (engaged) in the next stretch of time; students who were off-task after confusion tended to report boredom or frustration next. In contrast,

frustration showed a very different profile. Frustrated students who went off-task ended up next being focused; frustrated students who went on-task ended up next being bored. Apparently it was best for the frustrated students to take some time off from the primary task (see also Baker et al., 2010). It remains to be seen whether these results replicate, but they do illustrate the interesting and sometimes counterintuitive interactions between moment-to-moment emotions and learning activities. It is conceivable that a scientific understanding of these interactions will be necessary for any model that attempts to predict and explain successful serious games.

Summary and Speculations

This chapter has reviewed the available research investigating moment-to-moment emotions that occur in advanced learning technologies that target deep learning during relatively short, 1-2 hour time sessions. The primary learning-centered emotions are confusion, frustration, boredom, and engagement/flow, with occasional moments of curiosity, happiness, delight and surprise, and anxiety when students are preparing for tests. These emotions can be identified by the student, peers, teachers, and trained experts, but the different judges show modest agreement. There are automated methods of classifying emotions from the channels of tutorial dialogue history, language, speech, facial expressions, and body posture. The duration of emotions is longer for boredom, engagement/flow, and confusion than delight and surprise, with frustration in between. The occurrence and transitions between emotions are explained reasonably well by a cognitive disequilibrium theoretical framework. More specifically, the student experiences impasses that trigger cognitive disequilibrium and confusion. Confusion might be resolved and equilibrium restored; alternatively, unresolved confusion and persistent failure leads to frustration, boredom, and eventual disengagement. Engagement/flow occurs when the student is at the optimal level of challenge and manages to handle impasses that arise. There appears to be a causal relationship between cognitive disequilibrium and confusion, which in turn has a causal link to thoughtful

reasoning and deeper learning. A number of learning environments have been developed that track, manipulate, and respond to students' emotions in order to promote deep learning. This chapter focused primarily on three of these learning environments: Affective AutoTutor, dialogues with agents similar to the serious game Operation ARIES, and the serious game Crystal Islands. Projects were conducted that systematically tracked learner emotions and tested whether learning is improved by manipulating emotions or by adaptively responding to the student emotions.

The research discussed in this chapter provides an initial sketch of moment-to-moment emotions during complex learning, but more research is needed on so many levels. The occurrence, duration, and sequencing of moment-to-moment emotions undoubtedly depend on characteristics of the student, the learning environment, and social context so future research needs to document such differences. A broader array of emotions is expected in the following example contexts:

- (1) Hours or days before a major test in courses that span a semester or year. In addition to anxiety, there should be irritation, anger, and other emotions associated with high stress.
- (2) Social interaction in a classroom or smaller groups. Pride, shame, embarrassment, and many other social emotions would be expected.
- (3) Writing a difficult paper under a deadline or high stakes. Rage is likely for those with writer's block whereas a genuine flow experience occurs for the more gifted writers.

The traits of students are needed to predict what emotions occur in these situations, as been documented over decades of research (Linnenbrink, 2007; Pekrun, 2006).

The cognitive disequilibrium framework is a good start in accounting for the emotions that occur in advanced learning environments that target deep learning. However, there needs to be a systematic investigation of how components in the framework are influenced by individual differences among students with respect to subject matter knowledge, general reasoning skills, academic risk taking, intrinsic motivation, persistence, emotional intelligence, self-concept, and the

list goes on. These individual differences are undoubtedly mediating or moderating variables in the system, but this needs to be documented. For example, available evidence suggests that confusion is a pivotal emotion that sometimes leads to deeper learning, but there is uncertainty how particular types of students handle the confusion. Some students quickly escape confusion and conclude they are not very good at the subject matter; other students embrace confusion as a challenge to be conquered. There is the prospect of scaling the zone of optimal confusion for individual students. The learning technology would need to detect and be sensitive to these differences among students. Students who are prone to escape confusion will presumably need encouragement and good hints whereas those who embrace confusion will benefit from a steeper gradient of challenge. Such interactions among emotions, student characteristics, and technological features await future research.

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Figure 1. Cognitive Disequilibrium Framework.

