

Chapter 12: Emotional Learning Analytics

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ABSTRACT

This chapter discusses the ubiquity and importance of emotion to learning. It argues substantial progress can be made by coupling discovery-oriented, data-driven, analytic methods of learning analytics and educational data mining with theoretical advances and methodologies from the affective and learning sciences. Core, emerging, and future themes of research at the intersection of these areas are discussed.

Keywords: Affect, affective science, affective computing, educational data mining, learning analytics

At the recommendation of a reviewer of one of my papers [15], I recently sought to learn a statistical method called generalized additive mixed models (GAMMs) [48]. At first, I was mildly *displeased* at the thought of having to do more work on this paper. I downloaded a recommended paper with some eye-catching graphics, which piqued my *curiosity* and motivated me to explore further. This quickly turned into *interest* as I read more, and eventually into *excitement* when I realized the power of the approach. This motivated me to slog through the technical details, which led to *confusion* and *frustration* when things did not make sense, and *delight* when I made progress. When I attempted to apply the method to my data, I felt more *confusion* and *frustration*, interspersed with *hope*, *delight*, and *happiness*. I eventually got it working and wrote the results. When I was done, I felt *contentment*, *relief*, and a bit of *pride*.

As this example illustrates, emotion pervades the learning process. This is not unique to learning as much cognition is tinged with emotion. Emotions are not always consciously experienced [54], but they exist and influence cognition nonetheless. Also, emotions do not occur in a vacuum; they are deeply intertwined within the social fabric of learning. Students experience a range of emotions during learning. Pekrun & Stephens [57] call these “academic emotions” and group them into four categories. *Achievement* emotions are linked to learning activities (homework, taking a test) and outcomes (success, failure). *Topic* emotions are aligned with the learning content (empathy for a protagonist). *Social* emotions such as pride, shame, and jealousy occur because education requires interacting with others. Finally, *epistemic* emotions arise in the course of cognitive processing, such as confusion in the face of an impasse.

Emotions are not merely incidental; they may have evolved to serve specific functions [23, 69]. For example, emotions perform *signaling functions* [66] by highlight-

ing problems with knowledge (confusion), problems with stimulation (boredom), concerns with impending performance (anxiety), and challenges not easily surpassed (frustration). They perform *evaluative functions* by serving as the currency by which people appraise an event in terms of its value, goal relevance, and goal congruence [38]. Emotions perform *modulation functions* by changing cognitive focus; negative emotions engender narrow, bottom-up, and focused processing [8, 66] compared to positive emotions, which facilitate broader, top-down, generative processing [29, 37]. Emotions pervade thought through their effects on memory, problem solving, decision making, and other facets of cognition (see [12] for a review).

What exactly is an emotion? Truth be told, we do not really know, or at least we do not fully agree [38]. This can be readily inferred from recent debates on the psychological underpinnings of emotion. Fortunately, there is general agreement on the following key points. Emotions are conceptual or experienced entities arising from brain–body–environment interactions. However, you won’t find them by looking in the brain, body, or environment. Instead, emotions emerge [46] when organism–environment interactions trigger changes across multiple time scales and at multiple levels—neurobiological, physiological, behavioral, and subjective. The emotion is reflected in these changes in a manner modulated by previous experience and the ongoing situational context. The same emotional category (e.g., anxiety) will manifest differently based on a triggering event [69], the specific biological/cognitive/metacognitive processes involved [33, 50], and sociocultural influences [49, 56]. For example, an anxiety-inducing event will trigger distinct “episodes” of anxiety depending on the specific circumstance (public speaking, test taking), the temporal context (one day versus one minute before the speech), the neurobiological system (baseline arousal), and the social context (speaking in front of colleagues versus strangers). This level of

variability and ambiguity is expected because humans and their emotions are dynamic and adaptive. Rigid emotions have little evolutionary value as our environment is always changing.

Where do learning analytics (LA) and educational data mining (EDM) fit in? On one hand, given the key role of emotions in learning, attempts to analyze learning without considering emotion will be incomplete. On the other hand, given the ambiguity and complexity of emotional phenomena, attempts to study emotions during learning without the methods of LA and EDM will only yield shallow insights. There is a body of work adopting a data-driven analytic approach to study the incidence and influence of emotions on the processes and products of learning. In this chapter, we highlight some of the core, emerging, and future themes in this interdisciplinary research area.

First, a note on terminology. Emotion is related but not equivalent to motivation, attitudes, preferences, physiology, arousal, and a host of other constructs. Emotions are also distinct from moods and affective traits [62]. Emotion is not the same as a feeling. Hunger is a feeling but is not an emotion. There is some contention as to what constitutes an emotion. Anger is certainly an emotion, but what about confusion? Confusion has affective components (feelings of being confused, characteristic facial expressions; [18], but there is debate as to whether it is an emotion [34, 63]. In the remainder of this chapter, we use the more inclusive term *affective state* rather than the more restrictive term *emotion*.

CORE THEMES

We selected the following themes to highlight the use of LA/EDM methods to study affect during learning. We also deeply review a few exemplary studies within each theme rather than cursorily reviewing many studies. This means many excellent studies go unmentioned, but we leave it to the reader to explore the body of work within each theme. When available, we recommend review papers to facilitate this process.

0.1 Affect Detection from Student Activity Data

Affective states cannot be directly measured because they are conceptual entities. Because they emerge from environment–person interactions and influence action by modulating cognition, it should be possible to infer affect by analyzing context and learner actions. This approach, referred to as “interaction-based,” “log-file based,” or “sensor-free” affect detection has a decade-long history [1, 16](and was recently reviewed by [7]).

As an example, Pardos, Baker, San Pedro, Gowda, & Gowda [55] developed affect detectors for ASSISTments, an intelligent tutoring system (ITS) for middle- and high-school mathematics [60]. The authors collected training data from 229 students while they used ASSISTments in school computer labs. Human observers recorded affect as students interacted with ASSISTments using the

Baker-Rodrigo Observation Method Protocol (BROMP) [52]. According to this protocol, trained observers make live annotations of affect based on observable behavior, including explicit actions towards the software’s interface, interactions with peers and teachers, body movements, gestures, and facial expressions. The observers coded four affective states (boredom, frustration, engaged concentration, and confusion) and two behaviors (going off-task and gaming the system¹). Supervised learning techniques were used to discriminate each affective state from other states (e.g., bored versus others) using features extracted from ASSISTments log files (performance on problems, hint requests, response times). Accuracy for detecting affective states ranged from .632 to .678 (measured with the A-prime metric, similar to AUROC) for affect and .802 to .819 for behaviors. The classifier was validated in a manner ensuring generalizability to new students from the same population by ensuring each student’s data appears only in the training or the testing data. Pardos et al. [55] provided preliminary evidence on the predictive validity of their detectors. This was done by applying the detectors on log files from a different set of 1,393 students who interacted with ASSISTments several years earlier. Automatically measured affect and behavior moderately correlated with standardized test scores ($0.09 < |r| < 0.45$).

Further, San Pedro, Baker, Bowers, & Heffernan [65] attempted to predict college enrollment based on the automatic detectors. They applied the detectors to existing log files from 3,707 students who interacted with ASSISTments from 2004 to 2009. College enrollment information for these students was obtained from the National Student Clearinghouse. Automatically measured affective states were significant predictors of college enrollment several years later, which is a rather impressive finding.

More recently, Hutt, Grafsgaard, & D’Mello [36] developed a sensor-free measure of student engagement with an eye towards scalability. The research was conducted in the context of Algebra Nation, an online math learning platform supporting over 150,000 diverse students studying Algebra 1, Algebra 2, and Geometry. The researchers collected a large-scale dataset of 69,174 students who used Algebra Nation as part of their regular math classes for a semester and used experience sampling to collect 133,966 self-reports of 18 affective states (e.g., boredom, confusion, mind wandering, curiosity) related to engagement. They identified 22 generic activity features (viewing a video, pausing a video, taking a quiz) extracted from Algebra Nation log files in 5-minute windows prior to a self-report survey. These features do not require specialized sensors and are domain- and system-independent. They trained supervised learning models to predict each affective state from the features. Prediction accuracies (Spearman’s rho, a correlation coefficient ranging from -1 to 1), were modest and ranged from .08 (for surprise) to .34 (for happiness), with a mean of .25.

The researchers tested the generalizability of the engage-

¹[6] define gaming the system as, “attempting to succeed in an educational environment by exploiting properties of the system rather than by learning the material and trying to use that knowledge to answer correctly” (pp. 1-2)

ment models in several ways. First, they showed the models trained on Algebra students generalized to a different data set of Geometry students ($n = 28,458$) on the same platform. Jensen, Hutt, & D'Mello [41] demonstrated the models' generalizability to clusters of students based on typical platform use and demographic features. They found models trained on one group performed similarly well when tested on the other groups, although there was a small advantage of training multiple individual sub-population models compared to a general (all-population) model. These results show the promise of scaling up sensor-free methods to detect engagement on the largest and most heterogeneous student sample to date.

0.2 Affect Detection from Bodily Signals

Affect is an embodied phenomenon in that it activates bodily response systems for action. Signals of these bodily responses should make it possible to infer learner affect (a latent variable) from machine-readable bodily signals (observables). There is a rich body of work on the use of bodily signals to detect affect as discussed in a number of reviews [11, 20, 75]. Research has historically focused on interactions in controlled environments, but researchers have begun to take this work into the real world, specifically computer-enabled classrooms. The study reviewed next reflects one such effort by our research group and collaborators, but the reader is directed to Arroyo et al. [2] for their pioneering work on affect detection in computer-enabled classrooms.

Bosch, D'Mello, Ocumpaugh, Baker, & Shute [10] studied automated detection of affect from facial features in a noisy real-world setting of a computer-enabled classroom. In this study, 137 middle and high school students played a conceptual physics educational game called Physics Playground [67] in small groups for 1.5 to 2 hours across two days as part of their regular physics classes. Trained observers made live annotations of boredom, confusion, frustration, engaged concentration, and delight using the BROMP protocol. The observers also noted when students went off-task.

Videos of students' faces and upper bodies were recorded during game-play and synchronized with the affect annotations. The videos were processed using the FACET computer-vision program [26], which provides estimates of the likelihood of 19 facial action units [25] (e.g., raised brow, tightened lips), head pose, and position (Figure 1). Body movement was also estimated from the videos using motion filtering algorithms [44] (Figure 2). Supervised learning methods were then used to build detectors of each affective state (e.g., bored vs. other states) using both facial expressions and bodily movements. The detectors were moderately successful with accuracies (quantified by AUROC) ranging from .610 to .867 for affect and .816 for off-task behaviors. Follow-up analyses confirmed the affect detectors generalized across students, multiple days, class periods, and across different genders and ethnicities.

One limitation of the face-based affect detectors is they are only applicable when the face can be automatically detected in the video stream. This is not always the case

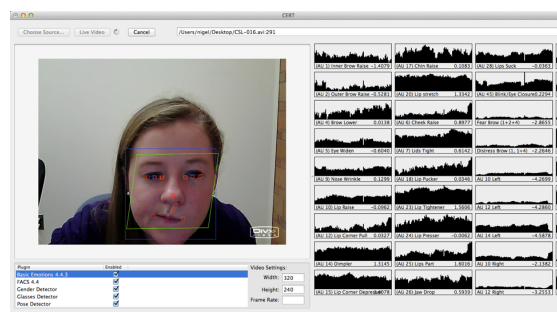


Figure 1: Automatic tracking of facial features using the Computer Expression Recognition Toolbox. The graphs on the right show likelihoods of activation of facial features.

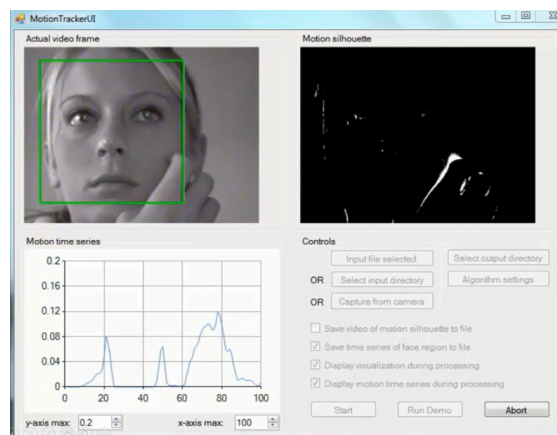


Figure 2: Automatic tracking of body movement from video using motion silhouettes. The image on the right displays the areas of movement from the video playing on the left. The graph on the bottom shows the amount of movement over time.

due to excessive movement, occlusion, poor lighting, and other factors. In fact, the face-based affect detectors were only applicable to 65% of the cases. To address this, Bosch, Chen, D'Mello, Baker, & Shute [9] combined interaction-based and face-based detection via decision-level fusion. The interaction-based detectors were less accurate than the face-based detectors (Kai et al., [42]), but were applicable to almost all of the cases. By combining the two, the detectors could be applied to 98% of the cases, with only a small reduction (<5% difference) in accuracy compared to face-based detection.

0.3 Integrating Affect Models in Affect-Aware Learning Technologies

The interaction- and bodily-based affect detectors just discussed are tangible artifacts that can be instrumented to provide real-time assessments of student affect during interactions with a learning technology. This affords the exciting possibility of closing the loop by dynamically responding to the sensed affect. The aim of such affect-aware learning technologies is to expand the bandwidth of

adaptivity of current learning technologies by responding to what students feel in addition to what they think and do (see [22] for a review). Here, we highlight two such systems, the Affective AutoTutor [17] and UNC-ITSPOKE [28].

Affective AutoTutor (see Figure 3) is a modified version of AutoTutor — a conversational ITS that helps students develop mastery on difficult topics in Newtonian physics, computer literacy, and scientific reasoning by holding a mixed-initiative dialog in natural language [31]. The original AutoTutor system has a set of fuzzy production rules sensitive to the cognitive states of the learner. The Affective AutoTutor augments these rules to be sensitive to assessments of learners' changing affective states, specifically boredom, confusion, and frustration. The affective states are sensed by automatically monitoring interaction patterns, gross body movements, and facial features [17]. The Affective AutoTutor responds with empathetic, encouraging, and motivational dialog-moves along with an avatar's emotional displays. For example, the tutor 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." The affective responses are accompanied by appropriate emotional facial expressions and emotionally modulated speech (e.g., synthesized empathy or encouragement).

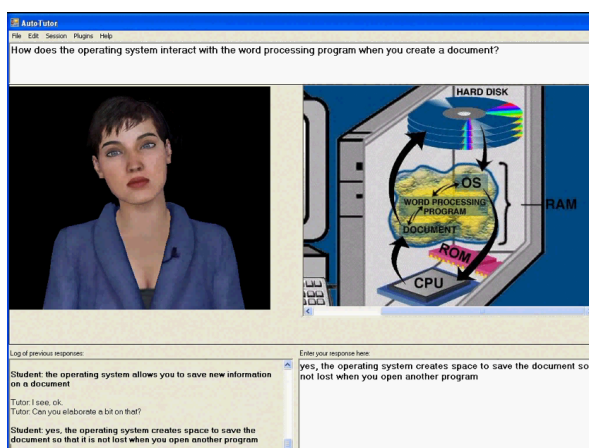


Figure 3: Affective AutoTutor: an ITS with conversational dialogs that automatically detects and responds to learners' boredom, confusion, and frustration.

The effectiveness of Affective AutoTutor over the original non-affective AutoTutor was tested in a between-subjects experiment where 84 learners were randomly assigned to two 30-minute learning sessions with an affective-aware or non-affective tutor [21]. The results indicated the affective tutor helped learning for low-domain knowledge learners during the second 30-minute learning session. The affective tutor was less effective at promoting learning for high-domain knowledge learners and during the first 30-minute session. Importantly, learning gains increased from Session 1 to Session 2 with the affective tutor whereas they plateaued with the non-affective tutor. Learners who interacted with the affective tutor also

demonstrated improved performance on a subsequent transfer test. A follow-up analysis indicated learners' perceptions of how closely the computer tutors resembled human tutors increased across learning sessions, related to the quality of tutor feedback, and powerfully predicted learning [19]. The positive change in perceptions was greater for the affective tutor.

As a second example, consider UNC-ITSPOKE [28], a speech-enabled ITS for physics which automatically detects and responds to learners' certainty/uncertainty in addition to the correctness/incorrectness of their spoken responses. Uncertainty detection was performed by extracting and analyzing acoustic-prosodic features in learners' spoken responses along with lexical and dialog-based features. UNC-ITSPOKE responded to uncertainty when the learner was correct but uncertain about the response. The response strategy involved launching explanation-based sub-dialogs that provided added instruction to remediate the uncertainty. This could involve additional follow-up questions (for more difficult content) or simply the assertion of the correct information with elaborated explanations (for easier content).

Forbes-Riley & Litman [28] compared learning outcomes of 72 learners who were randomly assigned to receive adaptive responses to uncertainty (adaptive condition), no responses to uncertainty (non-adaptive control condition), or random responses to uncertainty (random control condition). In this later condition, the added tutorial content from the sub-dialogs was given for a random set of turns to control for the additional tutoring. The results indicated the adaptive condition achieved slightly (but not significantly) higher learning outcomes than the other conditions. The findings revealed it was perhaps not the presence or absence of adaptive responses to uncertainty, but the number of adaptive responses that correlated with learning outcomes.

1 EMERGING THEMES

Research at the intersection of emotions, learning, LA, and EDM, has typically focused on one-on-one learning with an ITS [28, 32, 73], educational games [13, 43, 64], or interfaces that support basic competencies like reading and problem solving [21, 45]. Although these basic lines of research are quite active, recent work has focused on analyzing affect across interaction contexts that more closely reflect the broader sociocultural context surrounding learning. We briefly describe four themes of research to illustrate a few exciting developments.

1.1 Affect-Based Predictors of Engagement and Dropout

Indicators of potential dropout or poor grades and corresponding early intervention systems are some of the "killer apps" of LA and EDM [39]. Most systems in authentic settings focus on academic performance data, demographics, and availability of financial assistance. These factors are undoubtedly important, but there are likely

alternate factors that come into play. With this in mind, Tze, Daniels, Buhr, & Le [70] identified affective profiles in a Massive Open Online Course (MOOC). They found these different profiles were associated with varying levels of cognitive, behavioral, and social engagement with the course. For example, profiles with lower levels of boredom and guilt were associated with higher engagement with course content and profiles with high anxiety were associated with higher social engagement. Additionally, Dillon et al. [24] analyzed frequently occurring affective states in a MOOC and found states such as anxiety, confusion, frustration, and hope were positively associated with dropout.

1.2 Sentiment Analysis of Discussion Forums

Language often communicates feelings. Hence, sentiment analysis and opinion mining techniques (Pang & Lee, 2008) have considerable potential for studying how students' thoughts about a learning experience predict relevant behaviors like attrition. In line with this, Wen, Yang, & Rosé [72], applied sentiment analysis techniques to student posts on three MOOCs. They observed a negative correlation between dropout and the ratio of positive to negative posts. More recently, Xing, Tang, & Pei [74] expanded this analysis to specific academic achievement emotions. They found a student's exposure to classmates' negative emotions in discussions was the best predictor of future dropout.

1.3 Classroom Analytics

Recent advances in sensing and signal processing technologies have made it possible to automatically model aspects of students' classroom experience that could previously only be obtained from self-reports and labor intensive human observations (such as BROMP). Hutt, Krasich, et al. [35] used eye-gaze features to predict mind wandering when high-school students used a biology ITS in their regular classroom. Models using eye-gaze data were incorporated into the tutoring system to provide real-time mind wandering estimates for evaluation and to drive interventions. On a different scale, Ramakrishnan, Ottmar, Locasale-crouch, & Whitehill [59] used classroom audio and video to automatically identify positive and negative classroom climate. Finally, Aslan et al. [3] developed a dashboard to alert teachers to student real-time behavioral (on- or off-task) and emotional (bored, satisfied, confused) engagement (Figure 4). By using the interface, teachers could focus on addressing student comprehension rather than discipline; additionally, students showed less increase in boredom over the semester. These analytics can then be used by teachers or students to improve engagement in the classroom, such as reviewing a topic when confusion is detected or redirecting focus when mind wandering occurs.

1.4 Teacher Analytics

Teachers should not be left out of the loop since their practices influence student affect and engagement. Unfortunately, quantifying teacher instructional practices relies on

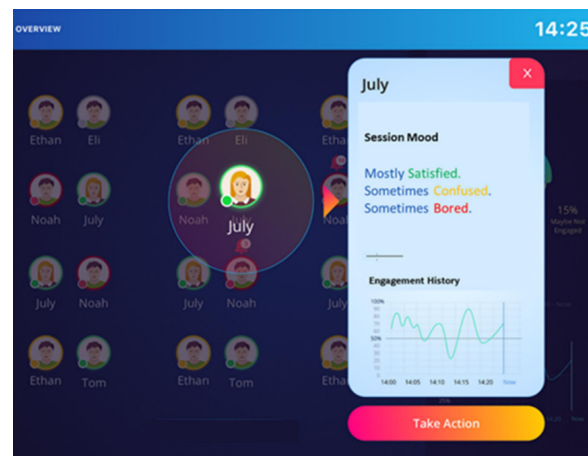


Figure 4: Student view of SEAT interface. Teachers can view overall class and student-specific analytics on engagement.

live observations in classrooms (e.g., Nystrand, Gamoran, Kachur, & Prendergast [51]), which makes the research difficult to scale. To address this, researchers are developing methods for automatic analysis of teacher instructional practices. In a pioneering study, Wang, Miller, & Cortina [71] recorded classroom audio in 1st to 3rd grade math classes and developed automatic methods to predict the level of discussions in these classes. This work was recently expanded to analyze specific discourse features in larger samples of middle-school classes in literature and language-arts. Jensen et al. [40] analyzed self-recorded teacher audio to automatically detect seven discourse features (e.g., asking questions, providing feedback), achieving a modest correlation with human-coded labels and demonstrating a robustness to audio quality changes. The next step in this line of work will be to use information on what teachers are doing to contextualize how students are feeling, which in turn influences what the students think, do, and learn.

2 FUTURE THEMES

Let us end by briefly highlighting some potential themes of future research. One promising area of research involves a detailed analysis of the emotional experience of learners and communities of learners across the extended time [35]. A second involves the study of emotion regulation during learning, especially whether LA/EDM methods can be used to identify different regulatory strategies [33], and encourage more beneficial ones (e.g., [5, 58, 68]). A third would jointly consider how emotion arises and shifts alongside attentional states of mindfulness, mind wandering, and flow [14]. A fourth addresses how “non-cognitive” [27] traits like grit, self-control, and diligence modulate learner emotions and regulation (e.g., [30, 47]). A fifth would monitor the occurrence and interaction of emotions of individual learners and the team as a whole during collaborative learning and collaborative problem solving [4, 61] given the importance of collaboration as a

critical 21st century skill [53].

Developments in these themes could then be applied to develop interventions that aim to make the learning experience more engaging and effective. This could take the form of redirecting attention, providing tools for emotion regulation, or adjusting instruction to meet student needs (i.e., scaffolding). An important challenge is developing “fail-soft” interventions; that is, if the analysis of a student’s current affective state is incorrect, then the resulting intervention will not negatively impact them.

Research to date has mainly focused on the achievement, epistemic, and topic emotions. However, an analysis of learning situated within sociocultural contexts must address the social emotions such as pride, shame, guilt, jealousy, and envy.

3 CONCLUSION

Learning is not a cold intellectual activity; it is nuanced with emotion. Emotions are not merely decorative, they influence our thoughts and behavior. However, emotion is a complex phenomenon with multiple components that dynamically unfold. Despite great strides in the fields of affective sciences and affective neuroscience, we need to know more about emotions, and more about emotions during learning. This does not imply we should refrain from modelling emotion until there is more theoretical clarity; we instead need to be mindful of what we are modelling when we say we are modelling emotion. We also need to embrace, rather than dilute, the complexity and ambiguity inherent in emotion. If anything, the discovery-oriented, data-driven, analytic methods of LA and EDM, especially when applied to data gathered in real-world settings, has the unique potential to advance both the science of learning and the science of emotion. It all begins by incorporating emotion into the analysis of learning.

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