An Affective Model of Interplay Between Emotions and Learning: Reengineering Educational Pedagogy—Building a *Learning Companion*

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Abstract

There is an interplay between emotions and learning, but this interaction is far more complex than previous theories have articulated. This article proffers a novel model by which to: a. conceptualize the impact of emotions upon learning, and then, b. build a working computer-based model that will recognize a learner's affective state and respond appropriately to it so that learning will proceed at an optimal pace.

1. Looking around then moving forward

> The extent to which emotional upsets can interfere with mental life is no news to teachers. Students who are anxious, angry, or depressed don't learn; people who are caught in these states do not take in information efficiently or deal with it well.
>
> **-** Daniel Goleman, *Emotional Intelligence*

Educators have emphasize conveying information and facts; rarely have they modeled the learning process. When teachers present material to the class, it is usually in a polished form that omits the natural steps of making mistakes (e.g., feeling confused), recovering from them (e.g., overcoming frustration), deconstructing what went wrong (e.g., not becoming dispirited), and starting over again (with hope and enthusiasm). Those who work in science, math, engineering, and technology (SMET) as professions know that learning naturally involves failure and a host of associated affective responses. Yet, educators of SMET learners have rarely illuminated these natural concomitants of the learning experience. The result is that when students see that they are not getting the facts right (on quizzes, exams, etc.), then they tend to believe that they are either 'not good at this,' 'can't do it,' or that they are simply 'stupid' when it comes to these subjects. What we fail to teach them is that all these feelings associated with various levels of failure are normal parts of learning, and that they can actually be helpful signals for *how* to learn better.

Expert teachers are very adept at recognizing and addressing the emotional state of learners and, based upon their observation they take some action that positively impacts learning. But what do these expert teachers 'see' and how do they decide upon a course of action? How do student who have strayed from learning return to productive path, such as the one that Csikszentmihalyi [1990] refers to as his "zone of flow"?

Skilled humans can assess emotional signals with varying degrees of accuracy, and researchers are beginning to make progress giving computers similar abilities at recognizing affective expressions. Although computers perform as well as people only in highly restricted domains, we believe that accurately identifying a learner's emotional/cognitive state is a critical indicator of how to assist the learner in achieving an understanding of learning process. We also assume that computers, sooner than later, will be more capable of recognizing human behaviors that lead to strong inferences about affective state.

We propose to build a computerized *Learning Companion* that will track the affective state of a learner through their learning journey. It will recognize cognitive-emotive state (affective state), and respond appropriately. We believe that the first task is to evolve new pedagogical models, which assess whether or not learning is proceeding at a healthy rate (or is stalled) and intervene appropriately; then these pedagogical models will be integrated into a computerized environment. Two issues face us, one is to research new educational pedagogy, and the other is a matter of building computerized mechanisms that will accurately and immediately recognize a learner's state by some ubiquitous method and activate an appropriate response.

Axis	-1. 0	-0. 5		0	+0. 5	+1. 0
Anxiety-Confidence	Anxiety	Worry	Discomfort	Comfort	Hopeful	Confident
Boredom-Fascination	Ennui	Boredom	Indifference	Interest	Curiosity	Intrigue
Frustration-Euphoria	Frustration	Puzzlement	Confusion	Insight	Enlightenment	Ephipany
Dispirited-Encouraged	Dispirited	Disappointed	Dissatisfied	Satisfied	Thrilled	Enthusiastic
Terror-Enchantment	Terror	Dread	Apprehension	Calm	Anticipatory	Excited

Figure 1 – Emotion sets possibly relevant to learning

2. Two sets of research results

This research project will have two sets of results. This paper offers the first set of results, which consists of our model and a research method to investigate the issue. A future paper will contain the results of the empirical research—the second set of results.

This paper will address two aspects of our current research. Section 3 will outline our theoretical frameworks and define our model (Figures 1 and 2). Section 4 will describe our empirical research methods.

3. Guiding theoretical frameworks: An ideal model of learning process

Before describing the model's dynamics, we should say something about the space of emotions it names. Previous emotion theories have proposed that there are from two to twenty basic or prototype emotions (see for example, Plutchik, 1980; Leidelmeijer, 1991). The four most common emotions appearing on the many theorists' lists are fear, anger, sadness, and joy. Plutchik [1980] distinguished among eight basic emotions: fear, anger, sorrow, joy, disgust, acceptance, anticipation, and surprise. Ekman [1992] has focused on a set of from six to eight basic emotions that have associated facial expressions. However, none of the existing frameworks seem to address emotions commonly seen in SMET learning experiences, some of which we have noted in Figure 1. Whether all of these are important, and whether the axes shown in Figure 1 are the "right" ones remains to be evaluated, and it will no doubt take many investigations before a "basic emotion set for learning" can be established. Such a set may be culturally different and will likely vary with developmental age as well. For example, it has been argued that infants come into this world only expressing interest, distress, and pleasure [Lewis, 1993] and that these three states provide sufficiently rich initial cues to the caregiver that she or he can scaffold the learning experience appropriately in response. We believe that skilled observant human tutors and mentors (teachers) react to assist students based on a few 'least common denominators' of affect as opposed to a large number of complex factors; thus, we expect that the space of emotions presented here might be simplified and refined further as we tease out which states are most important for shaping the companion's responses.

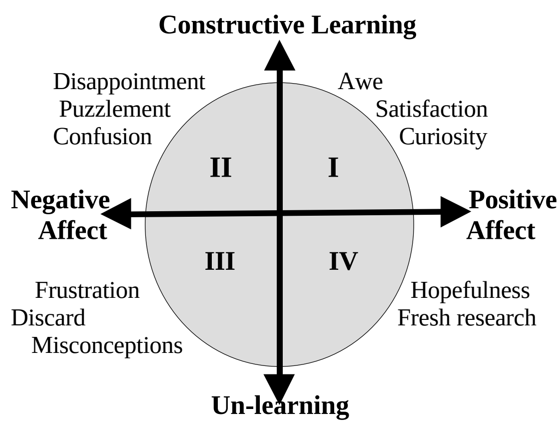

Figure 2 – Proposed model relating phases of learning to emotions in Figure 1

Nonetheless, we know that the labels we attach to human emotions are complex and can contain mixtures of the words here, as well as many words not shown here. The challenge, at least initially, is to see how our model and its hypothesis can do initially with a very small space of possibilities, since the smaller the set, the more likely we are to have greater classification success by the computer.

Figures 2 attempts to interweave the emotion axes shown in Figure 1 with the cognitive dynamics of the learning process. The horizontal axis is an Emotion Axis. It could be one of the specific axes from Figure 1, or it could symbolize the *n*-vector of all relevant emotion axes (thus allowing multi-dimensional combinations of emotions). The positive valence (more pleasurable) emotions are on the right; the negative valence (more unpleasant) emotions are on the left. The vertical axis is what we call the Learning Axis, and symbolizes the construction of knowledge upward, and the discarding of misconceptions downward. (Note: we do not see learning as being simply a process of constructing/deconstructing or adding/subtracting information; this terminology is merely a projection of one aspect of how people can think about learning. Other aspects could be similarly included along the Learning Axis.)

The student ideally begins in quadrant I or II: they might be curious and fascinated about a new topic of interest (quadrant I) or they might be puzzled and motivated to reduce confusion (quadrant II). In either case, they are in the top half of the space, if their focus is on constructing or testing knowledge. Movement happens in this space as learning proceeds. For example, when solving a puzzle in *The Incredible Machine*, a student gets an idea how to implement a solution and then builds its simulation. When she runs the simulation and it fails, she sees that her idea has some part that doesn't work – that needs to be deconstructed. At this point it is not uncommon for the student to move down into the lower half of the diagram (quadrant III) where emotions may be negative and the cognitive focus changes to eliminating some misconception. As she consolidates her knowledge—what works and what does not—with awareness of a sense of making progress, she may move to quadrant IV. Getting a fresh idea propels the student back into the upper half of the space, most likely quadrant I. Thus, a typical learning experience involves a range of emotions, moving the student around the space as they learn. Typically, movement would be in a counter-clockwise direction

If one visualizes a version of Figure 2 for each axis in Figure 1, then at any given instant, the student might be in multiple quadrants with respect to different axes. They might be in quadrant II with respect to feeling frustrated; and simultaneously in quadrant I with respect to interest level. It is important to recognize that a range of emotions occurs naturally in a real learning process, and it is not simply the case that the positive emotions are the good ones. We do not foresee trying to keep the student in quadrant I, but rather to help them see that the cyclic nature is natural in SMET learning, and that when they land in the negative half, it is only part of the cycle. Our aim is to help them to keep orbiting the loop, teaching them how to propel themselves especially after a setback.

A third axis (not shown), can be visualized as extending out of the plane of the page—the Knowledge Axis. If one visualizes the above dynamics of moving from quadrant I to II to III to IV as an orbit, then when this third dimension is added, one obtains the an excelsior spiral when evolving/developing knowledge. In the phase plane plot, time is parametric as the orbit is traversed in a counterclockwise direction. In quadrant I, anticipation and expectation are high, as the learner builds ideas and concepts and tries them out. Emotional mood decays over time, either from boredom or from disappointment. In quadrant II, the rate of construction of working knowledge diminishes, and negative emotions emerge as progress flags. In quadrant III, the learner discards misconceptions and ideas that didn't pan out, as the negative affect runs its course. In quadrant IV, the learner recovers hopefulness and positive attitude as the knowledge set is now cleared of unworkable and unproductive concepts, and the cycle begins anew. In building a complete and correct mental model associated with a learning opportunity, the learner may experience multiple cycles around the phase plane until completion of the learning exercise. Each orbit represents the time evolution of the learning cycle. (Note: the orbit doesn't close on itself, but gradually moves up the knowledge axis.)

4. Empirical research to validate the model

The second component of our project involves empirical research. The results of this part of the research will provide data that, when analyzed, will be used to control the actions of the fully automated version of the *Learning Companion*.

A number of 6-11 year old subjects will be video taped while individually playing the *Incredible Machine* or *Gizmos and Gadgets*. There are two video cameras gathering data. One camera is our version of IBM's *Blue Eyes* eye-tracking device. This camera focuses on the subject's eyes and tracks their movement as attempt to solve the puzzles presented by the software. Data from this camera will provide information of what the subject is *looking at*. The other camera, which is an off-the-shelf model, provides a split-screen view. One part of the split-screen will show the front of the subject's upper body and other part will also show the software as the subject sees it.

Data will be gathered from the *Blue Eyes* video tapes and correlated with the data from the split-screen video tapes. Data from the *Blue Eyes* tapes will provide eye-gaze data, which will be mapped onto data gathered from the split-screen video tapes. The split-screen data will be coded based upon three areas: surface level behavior, emotional state (a derivative of Figure 1 with numerical magnitude and valance as opposed to employing words, such a "ennui" or "hopeful"), and task/game-state.

We will further analyze data from the split-screen video camera to ascertain what Quadrant the learner is in (see Figure 2) and from that determine what the nature of the intervention will be (e.g., if a learner is in Quadrant I they might be given more '*rah-rah*,' '*you can do it*' kinds of interventions, if a learner were in Quadrant III and '*stuck*,' the intervention would be more of a hint/clue to se the learner back on the right path

From these results we expect to be able to embody a software-supported/driven *Blue Eyes*-like device. This device will, for example, intervene when a learner is not focused on the relevant part of the computer, or is focused completely outside the task area for a certain period of time, or their eye gaze is significantly quick/jerky for a certain time period. Such behavior would trigger an appropriate intervention.

Once this data has been analyzed and, hopefully, found to be valid, we expect to identify and track other facial movements in the same way we track and interpret other data as outlined in this paper.

Ultimately our expectation is to build an expanded *Blue Eyes*-like device that will be capable of 'seeing' other facial features such as eye brows, lips, and specific facial muscles—tracking them and reacting to them as they occur. We also expect the Learning Companion device to be able to make immediate software-driven evaluations of emotional state. These immediate evaluations would be made in the manner that coders of Ekman's [1997] Facial Action Coding System (FACS) now do over a period of some time. We expect to be able to interpret these trackable facial action as the FACS now does but we expect to be able to do this immediately as they occur.

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