RESTUCTURING EDUCATIONAL PEDAGOGY: A MODEL FOR DEEP CHANGE

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Numerous research studies support the claim that affect plays a critical role in decision-making and performance as it influences cognitive processes [1] [2] [3]. Despite this body of research there is insufficient theory within educational pedagogy to recognize and address the role and function of affect. The innovative models and theories that have been proposed to facilitate advancement in the field of educational pedagogy tend to focus on cognitive factors. Consequently, affective cues, which have a significant role, are often misinterpreted or ignored. We propose several new models for framing a dialogue leading to new insights and innovations that incorporate theories of affect into educational pedagogy.

Introduction

> The education establishment, including most of its research community, remains committed to the educational philosophy of the late nineteenth and early twentieth centuries, and so far none of those who challenge these hallowed traditions has been able to loosen the hold the educational establishment has on how children are taught.
>
> - Seymour Papert, *The Children's Machine*

Education traditionally has emphasized conveying a lot of information and facts, and has not 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 (feeling confused), recovering from them (overcoming frustration), deconstructing what went wrong (not becoming dispirited), and starting over again (with hope and maybe even enthusiasm). Learning naturally involves failure and a host of associated affective responses. However current educational pedagogy is lacking in certain areas and must be refocused and then reengineered.

But refocusing and reengineering educational pedagogy is a non-trivial task. To justify any change let alone this two-phased change, it must be shown that past research or legacy research is obsolete or irrelevant. To make our point we need to briefly review the nature and purpose of education over the years.

In Colonial days, schools were based upon 'recitation literacy' and from the World War I era forward schools were based upon 'extraction literacy' [4]. However a major shift in intellectual abilities necessitated the requirement for students of the new millennium to understand the state of their knowledge, be able to build upon it, improve it, and apply it appropriately. In short "[s]ociety envisions graduates of school systems who can identify and solve problems and make contributions to society through their lifetime—who display the qualities of 'adaptive expertise'" [5] [6]. Thus contemporary thought views learning as a person's ability to construct new knowledge based upon what they already know or believe to be true [7] [8] [9] [10] [11] [12] [13] [14] in short, the ability to perform model-based reasoning, reflection, and metacognition.

Schools seem to be functioning as well as they ever have, however the challenges and expectations have dramatically changed [15] [16]. Realizing that this education shift is happening is critical when redesigning the delivery of education to a learner. These new goals require changes in the redesign of learning environments. However current learning theory "does not provide a simple recipe for designing effective learning environments" given these changes [5]. "New developments in the science of learning raise important questions about the designs of learning environments…[the] general characteristics of learning environments…need to be examined in light of new developments in the science of learning" [5]. The basis of a model that will serve as a foundation for educational pedagogy should be embodied from such a mind-set (developing model-based thinkers). Educators should recognize the affective and cognitive state of the learner and respond in an appropriate manner (e.g., adjust the pace, direction, complexity).

The requisite for deep change in educational pedagogy would appear to involve:

?? a novel model that supports model-based reasoning, and,
?? an innovative learning cycle model that integrates/accounts for affect.

Refocusing Educational Pedagogy

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Current educational philosophy (Figure 2) tends to focus on the means to provide 'information' to the masses. This leads to standardized tests that draw out this 'information' and those who can extract it are judged to be 'educated' or 'intelligent'—but this is not intelligence, nor does it assess a person's knowledge, which is a person's ability to organize and appropriately apply information. This approach/belief merely develops a generation of people who will make great game-show contestants but does little to provide future adult citizens with needed problem-solving skills. It develops rule-based learners in an era that needs model-based reasoners and systems thinkers.

> However deep systemic change has never come easy [there is a] stubborn refusal to abandon the old ways…[when there is a] challenge to long-established procedures. The problem in education has an additional element. Most honest Schoolers are locked into the assumption that School's way is the only way because they have never seen or imaged convincing alternatives in the ability to impart certain kinds of knowledge [17].

To understand the need for a novel model, let us first examine the current educational model. The current model, as shown in Figure 2, begins with 'data,' which is a collection of answers to questions that the learner has not yet seen fit to ask or needs to ask. Such data becomes 'information' when it answers a question that the learner cares to ask. For the most part, a teacher, who must somehow motivate the student to care enough to seek the answers found in the data, supplies these questions. Studying is like 'panning for gold' where the answers are the 'nuggets' buried in a ton of otherwise uninteresting gravel. Once we have our 'nuggets of information' how do we organize them into a 'body of knowledge'? We may think of 'information' as the pieces of an unassembled jigsaw puzzle, whereas 'knowledge' is the assembled jigsaw puzzle. That is, the question-answer pairs are organized into a coherent structure, in the logical and natural order in which new questions arise as soon as old ones are answered.

The assembled 'jigsaw puzzle of knowledge' reveals a previously hidden picture—a 'big picture,' if you will. Or to put it another way, the assembled 'jigsaw puzzle of knowledge' is a tapestry into which is woven many otherwise hidden and previously unrevealed stories.

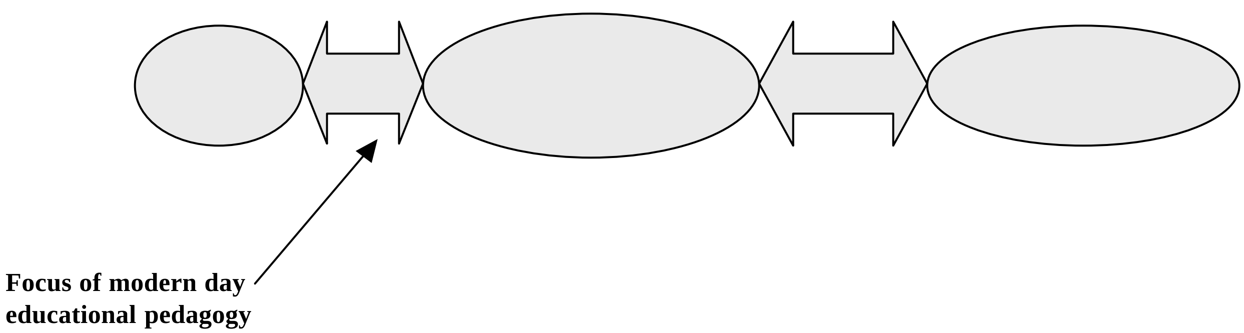

Fig. 2 – Old Model: Supports Rule-based Learning

The novel model shown below in Figure 3 goes beyond the current model shown in Figure 2. The focii of attention shifts to the construction of 'knowledge' and to the extraction of meaningful 'insights' from the 'big picture.' When 'knowledge' is coupled with a personal or cultural value system, 'wisdom' emerges. In other words, wisdom allows us to harness the power of knowledge for beneficial purposes.

'Wisdom' affords us the possibility of extracting the stories woven into the tapestry of knowledge. So from 'wisdom' we craft the bardic arts of story making and story telling. The ancients crafted myths and legends. These were the prototypical stories of their cultures, which were intended to impart 'wisdom.' A story is thus an anecdote drawn from the culture. A well-crafted anecdote or story has value both as an amusement and as a source of insight into the world from which it is drawn. And the plural of 'anecdote' is data—a collection of anecdotal stories or evidence. This observation closes the loop in Figure 3.

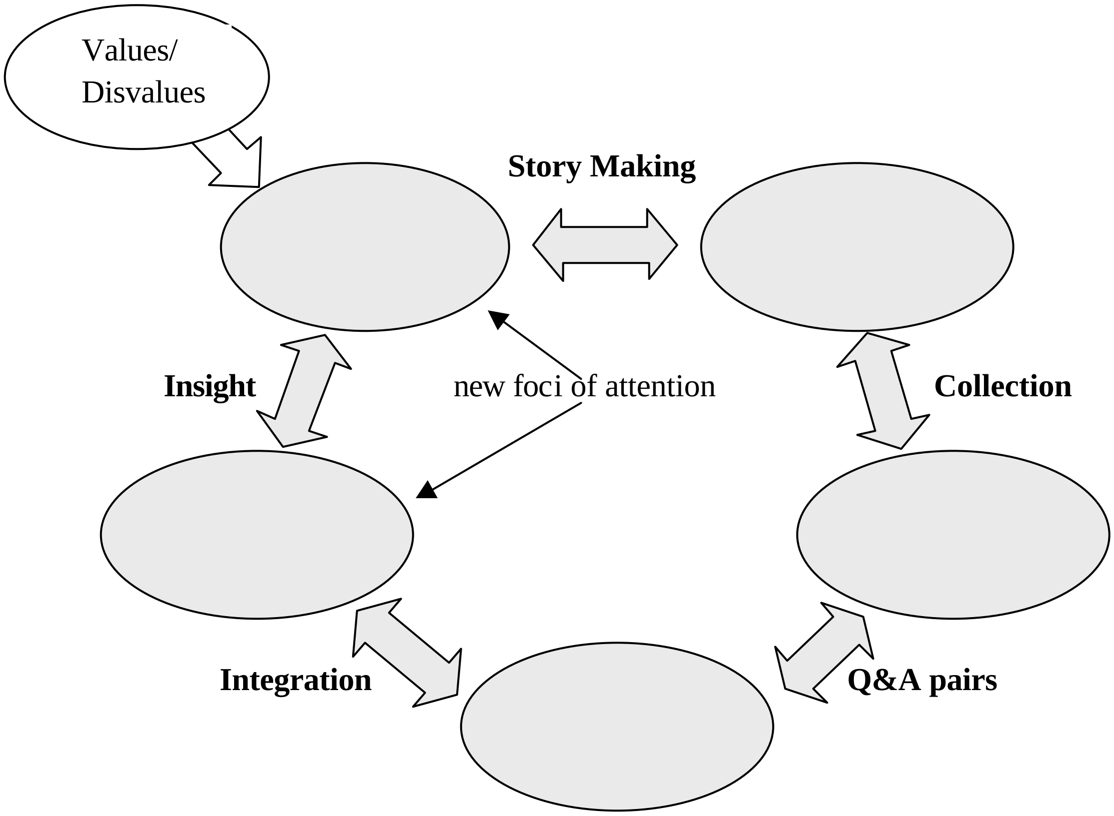

Fig. 3 ? New Model: Supports Model-based Reasoning

Figure 3 suggests a novel model that, on a fundamental level, supports an improved educational pedagogy. This will serve as a foundation for the next part of our model—how a learner's affective state should be incorporated into the overall model.

Affective State: Emotions and Learning

> 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*

In an attempt to install/build/re-engineer the current state of educational pedagogy, educators should first look to expert teachers who are adept at recognizing the emotional state of learners, and, based upon their observations, take some action that scaffolds learning in a positive manner. But what do these expert teachers *see* and how do they decide upon a course of action? How do students who have strayed from *learning* return to a productive path, such as the one that Csikszentmihalyi [18] refers to as the "zone of flow"?

This notion that a student's affective (emotional) state impacts learning and that appropriate intervention based upon that affective state would facilitate learning is the concept that we propose to explore in-depth.

To prove our point, note that skilled humans can assess emotional signals with varying degrees of precision. For example, researchers are beginning to make progress giving computers similar abilities to accurately recognize affective expressions [19] [20], facial expressions [21] [22] [23] [24] [25] [26], and gestural expression [27] [28]. Although computers only perform as well as people in highly restricted domains, we believe that:

?? accurately identifying a learner's cognitive-emotive state is a critical observation that will enable teachers to provide learners with an efficient and pleasurable learning experience, and,

?? unobtrusive highly accurate technology will be developed to accurately assess actions in less restricted domains [29].

Our own preliminary pilot studies with elementary school children suggest that a human observer can assess the affective emotional state of a student with reasonable reliability based on observation of facial expressions, gross body language, and the content and tone of speech. If the human observer is also acting in the role of coach or mentor, these assessments can be confirmed or refined by direct conversation (e.g. simply asking the student if she is confused or frustrated before offering to provide coaching or hints). Moreover, successful learning is frequently marked by an unmistakable elation, often jointly celebrated with "high fives." In some cases, the "Aha!" moment is so dramatic, it verges on the epiphanetic. One of the great joys for an educator is to bring a student to such a moment of triumph. But how can computers acquire this same level of proficiency as that of gifted coaches, mentors, and teachers?

Our first step is to offer a model of a learning cycle, which integrates affect. Figure 4 suggests six possible emotion axes that may arise in the course of learning. Figures 5a and 5b interweave the emotion axes shown in Figure 4 with the cognitive dynamics of the learning process.

In Figure 5, 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.

Axis	**-1. 0**	**-0. 5**		**0**	**+0. 5**	**+1. 0**
Anxiety-Confidence	Anxiety	Worry	Discomfort	Comfort	Hopefulness	Confidence
Ennui-Fascination	Ennui	Boredom	Indifference	Interest	Curiosity	Fascination
Frustration-Euphoria	Frustration	Puzzlement	Confusion	Insight	Enlightenment	Euphoria
Dispirited-Enthusiasm	Dispirited	Disappointed	Dissatisfied	Satisfied	Thrilled	Enthusiasm
Terror-Excitement	Terror	Dread	Apprehension	Calm	Anticipatory	Excitement
Humiliated-Proud	Humiliated	Embarrassed	Self-conscious	Pleased	Satisfied	Proud

Fig. 4 – Emotion sets possibly relevant to learning

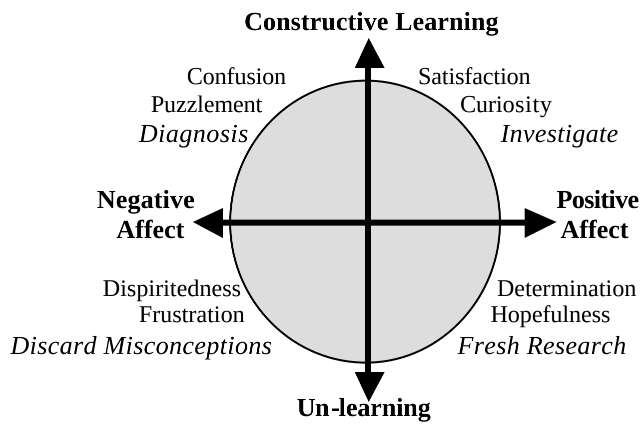

Fig. 5a – Four Quadrant model relating phases of learning to emotions in Figure 4

Students ideally begin in Quadrant I or II: they might be curious or 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 a bright idea how to implement a solution and then builds a simulation. If she runs the simulation and it fails, she sees that her idea has some part that doesn't work—that needs to be diagnosed and reconstructed. At this point the she may move down into the lower half of the diagram (Quadrant III) into the 'dark teatime of the soul' while discarding misconceptions and unproductive ideas. As she consolidates her knowledge—what works and what does not—with awareness of a sense of making progress, she advances to Quadrant IV. Getting another fresh idea propels the student back into the upper half of the space (Quadrant I). Thus, a typical learning experience involves a range of emotions, cycling her around the four quadrant cognitive-emotive space as she learn.

If one visualizes a version of Figure 5a (and Figure 5b) for each axis in Figure 4, 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 him see that the cyclic nature is natural in learning science, mathematics, engineering or technology (SMET), and that when he lands in the negative half, it is an inevitable part of the cycle. Our aim is to help students to keep orbiting the loop, teaching them to propel themselves, especially after a setback.

A third axis (not shown) can be envisioned as extending out of the plane of the page—the cumulative 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 an excelsior spiral. 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 wanes. In Quadrant III, as the negative affect runs its course, the learner discards misconceptions and ideas that didn't pan out. 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 until completion of the learning exercise. Note that the orbit doesn't close on itself, but gradually spirals around the cumulative knowledge axis.

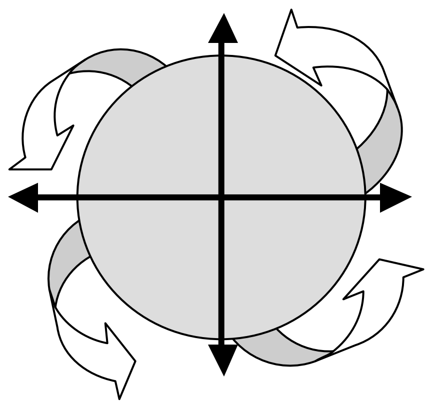

Fig. 5b – Circular and helical flow of emotion in Four Quadrant model

We are in the process of performing empirical research on this model. We have conducted several pilot research projects, which appear to confirm the model.

A brief discussion of our approach follows.

Affect Recognition

A great deal of research has been conducted to develop methods to infer affective state. Questionnaires have been used to infer such affect states as curiosity, interest, fatigue, and boredom (e.g., [30] [31] [33] utilized on-screen dialogue boxes with radio buttons to querying users about their frustration level. Although questionnaires can easily be administered, they have been criticized as being static and thus not able to recognize a change in affective state.

del Soldato [33] has been successful in gathering information about the subject's affective state via face-to-face dialogue. However studies involving verbalized assistance-on-demand have revealed a serious flaw in assuming that young readers are willing or able to ask for help [34].

Sentic modulation is a more dynamic and objective approach by which to assess a person's affective state [3]. This involves analyzing a person's emotional state by means of sensors such as cameras, microphones, strain gauges, and special wearable devices, which relate a constellation of patterns to the user's affective state.

Scheirer et al. [20] have built *Expression Glasses* that discriminate between upward eyebrow activity, which is indicative of positive emotions such as interest, and downward eyebrow activity, which is indicative of negative emotions such as confusion, or dissatisfaction. Healey [35] has used physiological sensors to infer stress levels in automobile drivers, and in a study that gathered data from four physiological signals.

The problem of automated affect recognition is still a difficult one. However Yacoob and Davis [36], Essa [26], and others have begun investigated the linkage between facial expression and emotional state. Other recent emotion recognition studies indicate that combining multiple modalities, such as audio and video, yield improved results [24] [27] [28]. However most of the studies have focused on deliberately expressed emotions as opposed to those that arise in natural situations (e.g., classroom learning).

Ekman [25] has developed the Facial Action Coding System (FACS), which is designed to recognize certain facial phonemes. These phonemes are classified as Action Units (AU) and depending on the summative AUs, a person's affective state is inferred.

Donato et al. [23] compared several techniques, which included optical flow, principal component analysis, independent component analysis, local feature analysis and Gabor wavelet representation. The purpose of the study was to recognize eight single action units (AUs) and four AU combinations using image sequences that were manually aligned and free of head motions.

Yingli Tian et al. [37] have developed a system to recognize sixteen action units and any combination of those using facial feature tracking.

In addition to being able to accurately detect emotional and cognitive aspects of the learning experience, our aim is to unobtrusively detect cues such as posture, gesture, eye gaze, and facial expression. Rather than identifying exact emotional state continuously throughout a learning experience we expect to identify the surface level behaviors that suggest a transition from a productive on-goal state to an unproductive off-goal state, or vice versa.

Surface Level Behaviors to Infer Affect

Affective states in learning, such as interest, boredom, confusion, and excitement are accompanied by different posture patterns, gestures, eye-gaze, and facial expressions. Rich et al. [1994] have defined symbolic postures that convey a specific meaning about the actions of a user sitting in an office (e.g., interested, bored, thinking, relaxed, defensive, and confident). Leaning forward towards a computer screen might be a sign of attention—an on-task state—while slumping on the chair or fidgeting suggests frustration or boredom—an off-task state.

The direction of eye gaze is also an important signal to assess the learner's focus of attention. In an on-task state the focus of attention is mainly directed toward the problem the student is working on, whereas in an off-task state the eye-gaze might wander away from the task.

Facial expressions and head nods are also reliable indicators of affective state.

Approving head nods (Ekman's AU 6) and facial actions such as a smile (AU 12), tightening of eyelids while concentrating (AU 7), eyes widening (AU 5), and raising of eyebrows (AU 1+2) suggest interest, surprise, excitement (an on-task state), whereas head shakes, lowering of eyebrows (AU 1+4), nose wrinkling (AU 9) and depressing lower lip corner (AU 15) suggests the state off-task state.

Also appropriately directed activity on the mouse and keyboard can be a sign of engagement whereas no activity or sharp repetitive activities may be a sign of disengagement or irritation.

These surface level behaviors are loosely summarized in Table 1.

Whether all of these are consequential remains to be evaluated. That determination will be made by examining a variety of surface level behaviors related to the inference of a user's affective state while engaged in natural learning situations.

	On Task	*Off Task*
Posture	Leaning Forward, Sitting Upright	Slumping on the Chair, fidgeting
Eye-Gaze	Looking towards the problem	Looking everywhere else
Facial Expressions	Eyes Tightening (AU7), Widening (AU5), Raising Eyebrows (AU 1+2), Smile (AU6+12)	Lowering Eyebrow (AU1+4), Nose Wrinkling (AU9), Depressing lower lip corner (AU15)
Head Nod/ Head Shake	Up-Down Head Nod	Sideways Head Shake
Hand Movement	Typing, clicking mouse	Hands not on mouse/keyboard

Table 1. Surface Level Behaviors

Validating Ideas That Lead to Deep Change

> [The standard] method of controlled experimentation that evaluates an idea by implementing it, taking care to keep everything else the same, and measuring the result, may be an appropriate way to evaluate the effects of a small modification. However, it can tell us nothing about ideas that might lead to deep change.
>
> - Seymour Papert, *The Children's Machine*

How does one go about 'validating' ideas, theories, and models that might lead to deep structural change? It seems problematic to just implement an idea that will possibly lead to deep change and then expect to validate such deep change in a relatively brief period. Deep change can evolve and, more importantly, be initially validated by supportive appropriate arguments and analyses of those arguments. Then, over a lengthily period of organic evolution in close harmony with social evolution, the models/theory can be validated. Such a process will be guided more by the participant's intuitive belief than by the outcome of empirical research or other tests and measurements.

Our model for deep change in educational pedagogy falls within Papert's admonition that the:

> most powerful resource for this process is exactly what is denied by objective psychology and the would-be science of education. Every one of us has built up a stock of intuitive, empathic, commonsense knowledge about learning. This knowledge comes into play when one recognizes something good about a learning experience without knowing the outcome. It seems obvious to me that every good teacher uses this kind of knowledge far more than test scores or other objective measurements in daily decisions about students. Perhaps the most important problem in education research is how to mobilize and strengthen such knowledge [17].

Our Four Quadrant Model (Figs. 5a and 5b), which espouses theories that may facilitate deep change in the application of affective computing to education, will be validated as it is incorporated into such artifacts as Intelligent Tutoring Systems, embodied conversational agents, and other cognitive machines.

Conclusion

> Why is there no word in English for the art of learning? Webster says that *pedagogy* means the art of teaching. What is missing is the parallel word for learning. In schools of education, courses on the art of teaching are simply listed as "methods." Everyone understands that the methods of importance in education are those of teaching—these courses supply what is thought to be needed to become a skilled teacher. But what about methods of learning?
>
> - Seymour Papert, *The Children's Machine*

Our models are inspired by theory often used to describe complex dynamic interactions in engineering systems. As such, they are not intended to explain how learning works, but rather to provide a framework for thinking and posing questions about the role of emotions in learning. As with any metaphor, the model has its limits. The model does not encompass all aspects of the complex interaction between emotions and learning, but begins to describe some of the key phenomena that needs to be considered in metacognition.

These models go beyond previous research studies not just in the range of emotions addressed, but also in an attempt to formalize an analytical model that describes the dynamics of a learner's emotional states, and does so in a language that supports metacognitive analysis.

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Bios

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