I Feel Your Pain: A Selective Review of Affect-Sensitive Instructional Strategies

Sidney D'Mello[1], Nathan Blanchard[1], Ryan Baker[2], Jaclyn Ocumpaugh[2], and Keith Brawner[3]
[1] University of Notre Dame; [2] Teachers College Columbia University; [3] U.S. Army Research Laboratory

INTRODUCTION

It is well known that students experience a range of affective states when interacting with a learning technology, be it an intelligent tutoring system (ITS), an educational game, a simulation environment, or even simpler interfaces that support foundational skills like reading comprehension and writing proficiency (see review in D'Mello, 2013). Positive affective states, such as contentment, delight, or pride may be triggered when a challenging problem is finally mastered. Negative affective states, such as the frustration, disappointment, or anger can occur when a learner is stuck at an impasse or in reaction to feedback from the learning environment. Learners' affect can be momentary, as in the occasional eureka moment when a major insight is obtained, prolonged in the case of boredom for a particular topic, or dispositional when the learner is enthused or disillusioned by a particular subject across a range of lessons or even a lifetime. We also know that affect is more than a mere incidental outcome that arises during learning, but can also indirectly influence learning outcomes by modulating cognitive processes in significant ways. For example, positive affective states can inspire a broader attentional focus, which is essential for creative problem solving (Clore & Huntsinger, 2007; Isen, 2008), but can also make a learner lose focus on the task at hand. On the other hand, negative affective states can be beneficial by focusing attention (Fiedler, 2001), but can hinder problem solving by triggering a form of tunnel vision when taken to an extreme.

Affect is still a complex mystery despite almost 150 years of scientific research. Decades of research in clinical psychology have revealed that humans have a relatively poor understanding of their own affective states, including how to regulate them. In a similar vein, considerable research in interpersonal communication, social dynamics, and cultural influences has indicated that people are not very apt at accurately perceiving and responding to the affective states of others, though we overestimate our ability to do so (Kelly & Metcalfe, 2011). So what is an ITS, with impoverished sensing capabilities, a shallow understanding of its environment, and a limited action repertoire to do? Should ITSs simply proclaim affect to be an insignificant or an insurmountable problem and proceed by attending to cognition as they have done in the first 20 years or so of their existence? Or should they tackle affect head-on due to its prominence and influence on cognition (and thereby learning), while at the same time being fully aware of the complexities involved in devising strategies to model affect? Our answer to the latter question is a resounding "yes," and in this chapter we discuss some affect-sensitive instructional strategies that "respond to affect." We do this by first discussing theoretical issues pertaining to affect and then by adopting a theoretical framework for the affective response strategies. The main contribution of this chapter is an exposition of six case studies, each featuring a unique affect-sensitive instructional strategy that has been developed and tested[1]. We follow this with a discussion of additional considerations for "ideal" affective strategies.

THEORETICAL FRAMEWORK

The goal of this section is to clarify key constructs, and identify an overarching theoretical framework in which to situate the affect-sensitive instructional strategies (also called affective strategies). We assume

[1] The reader is referred to Arroyo, Muldner, Burleson, and Woolf (in press) in this volume for a discussion on additional affective strategies.

that the reader is familiar with some basics of affect science, affective computing, and ITSs, so this section is relatively brief. Although some of the claims made below are generally accepted, others are still controversial and are being actively debated in the community. We sidestep all such debates by simply asserting our working definitions and assumptions.

States, Traits, Moods, and Emotions

Let us begin by clarifying what affect is and what it is not – at least from the perspective of this chapter. Affect is a state that arises from, influences, and is influenced by neurobiology, psychophysiology, and consciousness (Izard, 2010); though Ohman and Soares (1994) note that it can be unconsciously experienced as well. From a psychological perspective, which is the level of analysis we adopt in this chapter, an affective state is primarily a subjective feeling that influences cognition. Affect is related, but not equivalent to motivation, attitudes, preferences, physiology, arousal and a host of other related constructs that are often used to refer to it.

It is important to distinguish between affective traits, background moods, and emotions (Rosenberg, 1998). Affective traits are relatively stable, mostly unconscious predispositions towards particular emotional experiences. They operate by lowering the threshold for experiencing certain emotional states. As an example, a person with a hostile affective trait has a lower threshold for experiencing anger, but not necessarily other negative emotions. Moods also perform a threshold reduction function on emotional elicitation, but are considered to be more transitory and have a background influence on consciousness. Emotions are relatively brief, intense, states that occupy the forefront of consciousness, have significant physiological and behavioral manifestations, and rapidly prepare the bodily systems for action. Importantly, emotions are often directed at some object (a person, an event, or even a thought), while moods are more generalized. These different types of affective phenomena need to be addressed differently, hence, an instructional strategy that responds to affect should be mindful of whether it is targeting a trait, a mood, or an emotion. Most of the strategies discussed here focus on *emotions*, and the term *affective state* is used to refer to both bonafide emotions (e.g., disgust, anger) as well as affect-cognitive blends like confusion and boredom. Furthermore, the chapter assumes that the management of affective traits and long-lasting moods are currently beyond the scope of a tutoring system.

Another point worth mentioning pertains to the relationship between affect and learning outcomes. It is unlikely that there are direct causal links between affect and learning. Instead, affect indirectly influences learning by modulating cognition. For example, anxiety is unlikely to directly cause poorer learning, but rather negatively influences cognition, as is the case when working memory resources are consumed by anxiety-related thoughts (e.g., fear of failure). Therefore, it is advisable for an affect-regulation strategy to consider the cognitive processes influenced by affect and to alter these processes by directly changing the nature of the task or indirectly changing the underlying affect. This is the essence of an effective affective instructional strategy.

Emotion Regulation and Emotion Generation

It is useful to situate affect-sensitive instructional strategies within an overarching framework of affect. Numerous affect representation frameworks and theories exist, such as core affect (Russell, 2003), psychological construction (Barrett, 2009), basic emotions (Ekman, 1992), social perspectives (Parkinson, Fischer, & Manstead, 2004), and dynamical systems models (Lewis, 2005). Although each of these can serve as viable frameworks, we choose to situate our work within the *modal model* of emotion (Gross, 2008). This model is appealing because it addresses affective strategies that are both preventative (before affect arises) as well as reactive (after affect arises).

An affective state arises when an affect-eliciting situation is experienced, attended to, and cognitively appraised. The modal model of affect assumes five broad affective regulation strategies. Four of the regulatory strategies are anticipatory, while the fifth strategy is applicable after the affect is experienced.

Importantly, the processes of affect generation and affect regulation are not sequential, but demonstrate circular causality in that affect regulation can alter the affect generated, and the affect generated can trigger particular affect regulation strategies (Gross & Barrett, 2011).

The first two strategies, *situation selection* and *situation modification*, are regulatory strategies aimed at selecting or modifying contexts/situations that minimize or maximize the likelihood of experiencing certain affective states. Affect can also be regulated when a situation cannot be selected or modified via *attentional deployment*, which can involve either the avoidance of the affect-eliciting situation (distraction) or increased attention to the situation (rumination). Affect can be regulated even when a person's attention is focused on an event that has the potential to elicit a particular affective reaction. One such strategy is *cognitive change* (Dandoy & Goldstein, 1990), which involves changing the perceived meaning of a situation in order to alter its affective content. These four strategies are referred to as antecedent-focused affect regulation since they target the antecedents of affect. The fifth strategy, *response modulation*, occurs after the affective state is experienced and is referred to as response-focused affect regulation. Perhaps the most widely studied form of response modulation is *expressive suppression*, which involves a sustained effort to minimize the expression of affective behavior.

With varying levels of conscious awareness, learners continually engage in one or more of these strategies. They may select certain subjects based on perceived competence in order to alleviate anxiety (situation selection), choose topics within the selected subjects to maximize interest (situation modification), ignore states of confusion by focusing attention elsewhere or ruminate on negative feelings of frustration and despair (attentional deployment), alter attributes about failure (cognitive change), or suppress negative feelings when they arise (response modulation). An affective learning technology that operates within the processes of this framework has the following options: alter the situation (situation selection and situation modification), alter cognitions pertaining to the current situation (attentional deployment or cognitive change), or alter affective expression (response modification). The extent to which each of these strategies have been implemented and tested is discussed in the next section.

CASE STUDIES

We now turn to six case studies to discuss affect-sensitive instructional strategies with an emphasis on systems that have been tested. It should be noted that the research on affective instructional strategies, especially those that have been systematically tested, is in its infancy. To our best knowledge, the six case studies that we review reflect much of the existing work in this area. There have other implementations of the strategies discussed in these case studies and these are briefly discussed as well.

Table 1 provides a loose mapping between the case studies, instructional strategies, and the five components of the modal model. We consider preventative strategies that proactively alter appraisals to prevent negative affect, as well as reactive strategies that respond to negative affect when it inevitably arises. Strategies aimed at upregulating positive affect are also discussed, though these are more infrequent. General strategies that do not explicitly target affect (e.g., edutainment) are considered to be out of scope.

Table 1. Loose mapping between affective regulation strategies and components of the modal model

Case Study	Situation Selection	Situation Modification	Attentional Deployment	Cognitive Change	Response Modulation
Affective AutoTutor				encouraging and motivational messages	empathy and emotional displays
GazeTutor		content repetition	attentional reorientation messages		
UNC-ITSpoke		explanation-based subdialogs			
ConfusionTutor	contradictory trialogs				
Instructed Reappraisal				reappraisal	
Affective Learning Companion				affective support messages	nonverbal mirroring
Other Systems					false biofeedback

Affective AutoTutor: Empathetic, Encouraging, and Motivational Messages with Emotional Displays to Address Boredom, Confusion, and Frustration

Affective AutoTutor is a modified version of a conversational intelligent tutoring system 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 (Graesser, Chipman, Haynes, & Olney, 2005). The original AutoTutor system has a set of fuzzy production rules that are sensitive to the cognitive states of the learner. The Affective AutoTutor augments these rules to be sensitive to dynamic assessments of learners' affective states by addressing the presence of boredom, confusion, and frustration. The affective states are sensed by monitoring conversational cues and other discourse features, gross body movements, and facial features (D'Mello & Graesser, 2012a).

The Affective AutoTutor attempts to alter these negative states by incorporating perspectives from a number of psychological theories, including attribution theory (Weiner, 1986), cognitive disequilibrium during learning (Piaget, 1952), politeness (Brown & Levinson, 1987), and empathy (Lepper & Chabay, 1988), along with recommendations made by expert human tutors (see D'Mello et al., 2008 for details). The tutor responds with **empathetic, encouraging, and motivational dialog-moves** along with **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". A response to confusion would include attributing the source of confusion to the material: "Some of this *material* can be confusing. Just keep going and I am sure you will get it". These affective responses are accompanied by an appropriate emotional facial expression and emotionally modulated speech (e.g., synthesized empathy or encouragement). These displays are considered to be a form of response modulation due to the well-established emotion contagion effect (Adolphs, 2002).

The effectiveness of the 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 either tutor (D'Mello et al., 2010). The results indicated that 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 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 higher performance on subsequent transfer tests. A follow-up analysis into learners' perceptions of both tutors indicated that their perceptions of how closely the computer tutors resembled human tutors increased across learning sessions, was related to the quality of tutor feedback, and was a powerful predictor of learning (D'Mello & Graesser, 2012b). The positive change in perceptions was greater for the Affective tutor. In conclusion, this study indicated that the two affective strategies utilized by Affective AutoTutor, cognitive change and response modulation, improve learning, but this effect was only found for low-knowledge students.

GazeTutor: Messages to Reorienting Attention and Repetition of Unattended Content

Attentional engagement is a necessary condition for meaningful learning, so developing strategies for addressing attentional disengagement is likely to improve overall learning outcomes. Attentional disengagement can manifest when the learner voluntarily engages in off-task behavior (Baker, 2007) or experiences involuntary lapses in attention (mind wandering)[2]. Previous research has shown that attentional disengagement is typically a precursor to boredom (Eastwood, Frischen, Fenske, & Smilek, 2012), so strategies that target it are indirectly addressing boredom. The potential effects of an attentional reengagement strategy were addressed in a study of a dialog-based learning system, called the GazeTutor. The tutor used a commercial eye tracker to monitor learners' gaze patterns in order to identify when they had attentionally disengaged (D'Mello, Olney, Williams, & Hays, 2012). The tutor then attempted to re-engage learners with gaze-reorienting messages that instructed learners to pay attention to the tutor or to important parts of the interface (i.e., an explanatory image). In addition, the tutor would repeat the content that was ostensibly missed due to inattention. Hence, the instructional strategy used here consisted of **direct attentional reorientation messages with content repetition.**

The efficacy of GazeTutor in promoting motivation, engagement, and learning was tested in a within-subjects experiment where 48 learners were tutored on four biology topics with both gaze-reactive and non-gaze-reactive (control condition) versions of the tutor. The results indicated that GazeTutor was successful in dynamically reorienting learners' attentional patterns to the important areas of the interface. The effectiveness of gaze-orientation faded over time but did not entirely diminish. Although gaze-reactivity did not impact self-reported motivation and engagement, posttest scores for deep reasoning questions were higher when learners interacted with the gaze-sensitive tutor. Interestingly, individual differences in scholastic aptitude moderated the impact of gaze-reactivity on learning gains. Gaze-reactivity was associated with a small improvement in overall learning for learners with average scholastic aptitude, but learning gains were substantially higher for learners with high aptitude and somewhat lower for their counterparts. As such, this study demonstrates that the strategies of altering the situation through content repetition and altering cognition through attentional reorientation positively affected learning, more so for learners with high scholastic aptitude.

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[2] De Falco, Baker, and D'Mello (in press) in this volume discuss additional strategies to address disengaged behaviors.

UNC-ITSpoke: Responding to Uncertainty with Explanation-based Subdialogs

UNC-ITSPOKE is an ITS that was designed to examine whether automatic responses to learner uncertainty could improve learning outcomes (Forbes-Riley & Litman, 2007, 2009; Forbes-Riley & Litman, 2011). Uncertainty is a state that is similar to confusion and plays an important role in the process and products of learning. ITSPOKE is a speech-enabled ITS that teaches learners about various physics topics with spoken dialogs; student responses are automatically recognized with the Sphinx 2 Speech Recognizer (Litman et al., 2006). UNC-ITSPOKE extends the basic functionality of ITSPOKE with the capability to automatically detect and respond to learners' certainty/uncertainty in addition to correctness/incorrectness of their spoken responses. Uncertainty detection is performed by extracting and analyzing the acoustic-prosodic features in learners' spoken responses in conjunction with lexical and dialog-based features.

Responses to uncertainty occurred when the student was correct in their response but uncertain about the response. This was taken to signal an impasse because the student is unsure about the state of their knowledge despite being correct. The actual response strategy involved launching **explanation-based sub-dialogs** that provided added instruction to remediate the uncertainty. This might involve additional follow-up questions (for more difficult content) or simply asserting the correct information with elaborated explanations (for easier content).

In a recent study, Forbes-Riley and Litman (2011) compared learning outcomes between 72 learners who were randomly assigned to receive adaptive responses to uncertainty (adaptive condition), no responses to uncertainty (no adapt 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 in order to control for the additional tutoring. Results indicated that the adaptive condition achieved slightly (but not significantly) higher learning outcomes than the random and control conditions. The findings revealed that it was perhaps not the presence or absence of adaptive responses to uncertainty, but the number of adaptive responses that correlated with learning performance. Unfortunately, the biggest challenge was caused by errors in automatic uncertainty detection, which reduced the number of opportunities for adaptive responses. Thus, although the findings were somewhat mixed, Forbes-Riley and Litman (2011) conclude that there is merit in offering adaptive feedback to uncertainty, and that such feedback can improve learning outcomes. Further research, specifically in the area of automated uncertainty detection is required to improve the effectiveness of an affective strategy of explanation-based sub-dialogs as a form of situation modification.

ConfusionTutor: Inducing Productive Confusion with Counterfactual and Contradictory Information

UNC-ITSpoke views uncertainty and impasses as opportunities for learning, a view that is consistent with theories that highlight the benefits of impasses (VanLehn, Siler, Murray, Yamauchi, & Baggett, 2003), cognitive conflict (Limón, 2001), cognitive dissonance (Festinger, 1957), cognitive disequilibrium (Piaget, 1952), and socio-cognitive conflict (Mugny & Doise, 1978). Confusion is considered to be the affective signature of these states (D'Mello & Graesser, in press). Therefore, one hypothesis is that events that confuse learners might provide valuable learning opportunities because learners need to engage in deep cognitive activities in order to resolve their confusion. It is likely that the cognitive activities that accompany confusion resolution promote deeper learning, rather than the confusion itself.

The hypothesis that confusion can impact learning was tested by modifying an educational game, Operation ARA (Millis et al., 2011), to systematically induce confusion (D'Mello, Lehman, Pekrun, & Graesser, 2014). ARA teaches scientific research methods and critical thinking skills through a series of game modules, including those with two or more animated pedagogical agents. In the trialogs, a 3-way conversation transpired between the human student, a tutor-agent, and a student-agent. The tutor-agent was an expert on scientific inquiry whereas the student-agent was a peer of the human learner. A series of research case studies that have a crucial experimental design flaw with respect to proper scientific methodology was presented by one of the agents. Confusion was induced by manipulating whether or not the tutor-agent and/or the student-agent provided **counterfactual** information that **contradicted** the other agent during the trialog. The human learner was asked to intervene after each point of contradiction. If the human learner experienced uncertainty and was confused, this should be reflected in the incorrectness/uncertainty of his or her answer and on self-reported confusion. In some cases, the learner was presented with short instructional texts which contained information to assist in confusion resolution.

Two experiments, with 63 and 76 learners, confirmed that contradictions increased learners' confusion. Importantly, levels of confusion moderated the impact of the contradictions on learning. Specifically, the contradictions had no effect on learning when learners were not confused by the manipulations, whereas performance on multiple-choice posttests and on transfer tests was substantially higher when the contradictions were successful in confusing learners. This suggests that there are some benefits to inducing confusion if learners are *productively* instead of *hopelessly* confused. By productive confusion, we mean that the confusion is relevant to the learning content, the learner actively attends to the confusion by engaging in confusion-resolution activities, the learner has the capability to resolve the confusion, and the learning environment provides appropriate scaffolds when needed. In summary, this study showed that counterfactual and contradictory trialogs as a situation selection strategy can have significant positive impact on learning if properly directed.

Instructed Reappraisal to Increase Engagement and Positive Affect

A more recent attempt to understand emotion regulation, as defined by Gross (2008) as the physiological, behavioral, and cognitive processes that enables individuals to manage the experience and expression of emotions, is provided by Strain and D'Mello (in review). This study set out to investigate cognitive change, which involves changing the way one thinks about the situation to alter its emotional meaning. Cognitive reappraisal is suggested to be a key emotion regulation technique, yet little research in educational psychology has endeavored to understand whether cognitive change is effective during learning. Thus, the goal was to examine whether providing learners with instruction on cognitive reappraisal strategies would help them to effectively manage their emotional experiences (particularly boredom) during learning. If emotion regulation strategies are effective, then ITSs (especially those that are affect-sensitive) can encourage learners to adopt these strategies at appropriate moments.

The authors test a cognitive reappraisal strategy in the context of a 45-minute web-based self-paced learning session in which 93 participants were asked to learn about the U.S Constitution and Bill of Rights, answer simple text-based and more challenging inference questions, and report their affective states at multiple points. Participants were randomly assigned to one of three conditions: *instructed reappraisal* (IR), *error searching* (ES), or *control*. All participants were instructed that they would be reading the Constitution and Bill of Rights and answering easy and difficult questions about the material, to demonstrate that they are capable of learning a lot of information quickly and efficiently. Participants in the IR condition were asked to imagine that they were applying for a job as a copy-editor at a powerful law firm in their city. This imaginary situation involved them having to check the document for typos and grammatical errors to demonstrate their skill as copy-editors. By asking participants to imagine that they were applying for a job, it was expected that they would place more meaning on the task than if they were simply completing the task for a small payment. That is, instead of their default appraisal of reading a lengthy and boring document, they would **reappraise** the situation as being more relevant to the imagined desire to get the job. In contrast, participants in the ES condition were simply asked to perform the copy editing without the reappraisal component. Participants in the control condition received no special instructions about cognitive reappraisal or error searching.

Compared to the control condition, learners in the IR condition experienced more positive-activation affect (dimensionally assessed with self-reports of valence and arousal), higher engagement, lower confusion and frustration on discrete affect measures, and significantly higher learning outcomes on knowledge tests. The IR and ES conditions did not differ in arousal or engagement, but the IR condition reported significantly more positive valence, less confusion, and less frustration. The IR condition also significantly outperformed the ES condition on learning measures. This suggests the improved performance of the IR condition over the control condition was attributable to the use of the IR strategy, and not the task of error searching.

A follow-up experiment with 138 learners that compared the same IR strategy to an open-ended reappraisal (where learners adopt their own reappraisal strategy), a suppression strategy (where learners are asked to suppress all behavioral indicators of emotion), and the same control condition, found positive effects of reappraisal on positive affect, engagement, and learning (Strain & D'Mello, in review). Hence, the main conclusion is that cognitive change, even in the form of a vastly simplified reappraisal strategy used in these experiments, can be a successful method for regulating emotions and improving learning.

Affective Learning Companion with Nonverbal Mirroring and Affect Support

Burleson and Picard (2007) devised an affective strategy for an affective learning companion that helps students solve the Tower of Hanoi problem. The learning companion takes the form of an embodied conversational agent (ECA) and combines nonverbal mirroring with affective support. The **nonverbal mirroring** was accomplished by sensing learners' facial expressions, posture, electrodermal activity, and pressure exerted on the mouse. The ECA responded to this sensed data after a 4-second delay with similar facial expressions and postures, increased swaying in response to mouse pressure, and reddened skin tone to convey physiological arousal. The **affective support** intervention consisted of the ECA speaking messages that supported learners' meta-cognitive assessments of their ability to solve the problem, derived from incremental theories of intelligence (Dweck, 2006). These messages suggested that the mind is like a muscle that can be strengthened with effort.

An experiment with 61 children (11 to 13 years of age) was conducted to evaluate the affective learning companion. It employed a 2 × 2 between-subjects design where learners were assigned to an agent with affective support and nonverbal mirroring, task support with nonverbal mirroring, affective support with prerecorded nonverbal interaction, and task support with prerecorded nonverbal interaction. In the task support condition, the ECA provided messages pertaining to the task, but these messages did not address feelings or attempted to motivate learners. In the prerecorded nonverbal interaction condition, the ECA's nonverbal behaviors were driven by the behaviors of "average participants" from pilot studies.

The results did not yield any significant differences (main effects or interactions) on a range of outcome variables encompassing perseverance, formation of social bonds with the agent, frustration, intrinsic motivation, etc. However, exploratory follow-up-analyses did yield several interesting gender effects. For example, girls in the combined affective support plus nonverbal mirroring condition reported lower levels of frustration than girls who received each individual treatment (i.e., affective support with prerecorded nonverbal interaction or task support with nonverbal mirroring). There were additional interesting gender interactions, as discussed in Burleson and Picard (2007); however, the small sample size (roughly 7-8 per cell) warrants replication with a larger sample. The tentative results of this study appear to indicate that response modulation and cognitive change strategies can effectively be used to alter affective states, and that the learning gains induced by these strategies may be particularly effective for young girls.

Additional Implementations of Basic Strategies and Other Strategies

In addition to the six case-studies discussed in detail above, a few other studies of affective regulation strategies bear mentioning. Some systems make an inference of the underlying affective state, but do not directly attempt to detect affect. For example, Tsukahara and Ward (2001) varied the **acknowledgement** a tutor provided the student during a simple memory game by *inferring* affect based on student prosody. A small-scale user test (N = 13) indicated that users preferred this system compared to a control.

Similarly, Andallaza and Rodrigo (2013), made inferences of student affect based on number of steps taken to solve a problem and solving duration, and responded with **motivational** messages. An experiment with 80 learners did not yield any positive effects on learning but learners indicated that they preferred the affective system compared to controls. Recently, Kelly, Heffernan, D'Mello, Namais, and Strain (2013) studied the effect of **teacher-generated motivational videos** that emphasized the value of a difficult math exercise and the importance of exerting effort towards building competence during homework completion with ASSISTments, an ITS for middle school math. They found small effects on positive valence (Experiment 1 with N = 24) and improved homework completion rates (Experiment 2 with N = 60) compared to controls, but these results warrant replication with larger samples.

There has been considerable interest in using **empathy** as an affective response strategy. This has been studied by Kim, Baylor, and Shen (2007) on 56 pre-service teachers and McQuiggan, Robison, Phillips, and Lester (2008) on 35 college students in the context of CRYSTAL ISLAND, a narrative-centered educational game. A unique feature of these studies is that the interventions were triggered from self-reports, instead of automated affect detection. Some researchers also differentiate between different types of empathetic responses (McQuiggan et al., 2008; Moridis & Economides, 2012). **Parallel empathy** simply involves mirroring the learners affective state (e.g., displaying frustration when the learner is frustrated) whereas **reactive empathy** involves performing a deeper analysis of learner affect to converge upon an appropriate response that goes beyond simple affect mirroring (e.g., displaying sadness when a learner is frustrated).

Researchers have also considered inducing states of physiological arousal in order to increase metacognitive awareness and potentially learning. Strain, Azevedo, and D’Mello (2013) used a **false biofeedback paradigm**, where learners were presented with audio stimuli of accelerated or baseline heartbeats purportedly representing their own heart beats during a challenging learning task. They found that learners self-reported experiencing more positive activating affect, made more confident metacognitive judgments, and achieved better learning when they received biofeedback compared to no biofeedback. Interestingly, these effects were only discovered for challenging questions that required inference as opposed to simpler text-based questions, and type of biofeedback (accelerated vs. baseline) had no effect.

FUTURE CONSIDERATIONS

We now turn to additional issues of relevance to affect-sensitive instructional strategies, including the representation, dynamics, antecedents, and detection of affective states. Some of these aspects may be less feasible as research items in the short-term given the current nascent state of the field. Nevertheless, they might serve as fruitful avenues for future research as they are likely to contribute to more “ideal” affective instructional strategies.

Affective representations can be dimensional or discrete, a topic of intense debate that has important implications for affect-sensitive instructional strategies. Valence (positive to negative) and arousal (sleepy to active) are considered to be the primary affective dimensions (Russell, 2003), though researchers have argued for additional dimensions as well (Fontaine, Scherer, Roesch, & Ellsworth, 2007). Discrete affective states are usually represented as dichotomous variables (e.g., student is confused but not frustrated, bored, anxious, etc) or as ordinal variables (e.g., via Likert scales). Discrete (or categorical) representations are preferred over dimensional representations when devising affect-sensitive instructional strategies. For example, frustration and boredom are both negatively valenced, but the strategies needed to regulate the activating state of frustration are quite different than those needed for the deactivating state of boredom. However, an ITS is likely unable to differentiate between the two states using only valance and arousal. For this reason, discrete representations are better able to inform affective instructional strategies.

Affective dynamics, in the form of timing and intensity, are of singular importance. Some affective states are ephemeral (e.g., surprise, eureka moments), while others are more persistent (e.g., boredom, anxiety) (Baker, D'Mello, Rodrigo, & Graesser, 2010; D’Mello & Graesser, 2011). A state can also exhibit ephemeral properties in some situations while demonstrating persistence in others; these differences in temporal duration can differentially impact learning. For example, experiences of confusion that are immediately resolved are expected to have little to no effect on learning, whereas persistent confusion that is never resolved might be negatively related to learning (D'Mello & Graesser, in press). Timing and intensity of affect can also interact in striking ways. A long-lasting, but low-intensity state of anxiety might not be very impactful, but a single episode of intense embarrassment or anger can have long-lasting negative consequences (e.g., dislike for an ITS based in one unpleasant interaction can engender negative feelings towards an entire course). Hence, it is advisable for an affect-sensitive instructional strategy to be sensitive to the timing and intensity of affect.

Affect-inducing events have a singular effect on the affective states generated and how they are expressed. Thus, successfully regulating an affective state entails understanding the affect-inducing event and the appraisals of the event that gave rise to the state. Boredom offers a convenient example. According to Pekrun’s *control-value* theory of academic emotion, subjective appraisals of control and value of a learning activity are the critical predictors of boredom and other academic emotions (Pekrun, 2010). Subjective control pertains to the perceived influence that a learner has over the activity and its outcomes, while subjective value represents the perceived value of the activity. Boredom is expected to be heightened when learners perceive low value in the outcome of the activity, and both when control is too low (challenge exceeds skill) and too high (skill exceeds challenge). An intervention that attempts to reengage bored learners by emphasizing the value of the learning activity will miss its mark entirely when the underlying cause of boredom is due to a lack of control. It can even have negative consequences, as noted by Durik and Harackiewicz (2007) who found that informing low-competence students (low control) about the relevance of math material for their lives (value manipulation) actually undermined value because it was perceived as threatening. The important message here is that an effective affect-sensitive instructional strategy should be sensitive to the antecedents of the affective state in addition to the affective state itself.

Affect detection is usually a first step for affect-sensitive instructional strategies. Affect detection is perhaps the most actively explored subfield of affective computing (see reviews by Calvo & D’Mello, 2010; D'Mello & Kory, 2012; Zeng, Pantic, Roisman, & Huang, 2009), but like much of the affective sciences, is inherently imperfect and is unlikely to ever reach perfection. How can we tailor instructional strategies in anticipation of imperfect affect detection? In addition, we outlined additional considerations for affective instructional strategies in this section. We advocated a focus on discrete affect representations, an emphasis on the timing and intensity of affective states, and on considering the antecedents of affect while tailoring instructional strategies. These pose additional challenges for affect detectors that are now faced with the task of detecting intensity, duration, and antecedents, in addition to the already challenging task of basic affect detection. Therefore, progress in affect detection is essential before some of these “ideal” affect-sensitive instructional strategies can be effective.

CONCLUSIONS

Intelligent Tutoring Systems (ITSs) were devised to provide more fine-grained domain and student modeling, allowing instruction to be tailored in a more highly individualized manner than their computer-based learning predecessors (Psotka, Massey, & Mutter, 1988). Their effectiveness compared to other forms of instruction is impressive as documented in recent reviews and meta-analyses (Steenbergen-Hu & Cooper, in press; VanLehn, 2011), but this positive news has been tempered by the suggestion that improvements in the effectiveness of ITSs have somewhat leveled off, reaching what VanLehn (2008) refers to as the *interaction plateau*. Might this plateau be partially attributed to the fact that ITSs have traditionally focused on modeling cognition while largely ignored affect and motivation? If so, there might be the added benefits to improving ITS effectiveness by devising strategies to respond to these non-cognitive aspects of learning. Here, we considered the possibility of increasing the bandwidth of ITS adaptivity by modeling student affect.

This chapter described case studies of six systems that implemented twelve affect-sensitive instructional strategies: encouragement, motivational messages, empathy, emotional displays, attentional reorientation messages, content repetition, explanation-based subdialogs, contradictory trialogs, instructed reappraisal, affective support messages, nonverbal mirroring, and false biofeedback. These strategies are impressive in breadth as they cover cognitive, affective, motivational, nonverbal, and metacognitive aspects of learning. Systems that have implemented these strategies have had some success in terms of promoting positive outcomes like engagement, persistence, and learning. Although there was considerable variability in effectiveness of the affective strategies, one consistent finding is that effectiveness almost always varied as a function of differences in individual attributes (e.g., gender, prior knowledge, scholastic aptitude) and/or aspects of the learning session (e.g., content difficulty, outcome measure). This suggests that there are limits to the current one-size-fits-all approach, where variants of the same strategy are indiscriminately used for all learners and in all situations. The strategies need to be more focused by configuring them to be sensitive to learner attributes, to nuances of the learning session (affect-eliciting events), and to different manifestations of the same affective state (e.g., different types of boredom). This level of adaptivity will require continual improvements in automated affect sensing and context modeling, coupled with a deeper understanding of affect during learning. We consider this to be the next grand challenge for the field of affect-sensitive learning environments.

ACKNOWLEDGMENT

This research was supported by the National Science Foundation (NSF) (ITR 0325428, HCC 0834847, DRL 1235958) and the Bill & Melinda Gates Foundation. Any opinions, findings and conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agencies.

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