An Integrated Emotion-Aware Framework for Intelligent Tutoring Systems

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Abstract. This conceptual paper integrates empirical studies and existing conceptual work describing emotion regulation strategies deployed in intelligent tutoring systems and advances an integrated framework for the development and evaluation of emotion-aware systems.

Keywords: Emotions · Affect · Emotion regulation · Emotion-aware systems · Intelligent tutoring systems

1 An Integrated Emotion-Aware Framework

D'Mello and Graesser [1] provide a good starting dichotomy of emotion-aware systems by differentiating proactive from reactive system features. *Proactive* features represent components that induce or impede emotional states whereas *reactive features* are those that respond to states in real-time (typically negative states). The present framework elaborates upon these two types of features by mapping out their different components, dependencies, and interrelationships in order to capture and structure the rich and creative variety of ways ITS can support positive emotions.

1.1 Proactive Features

Proactive features can be classified as either user-adaptive or non-adaptive, where *adaptive* refers to whether the ITS uses information it has collected about the user to make changes to any part of its interaction with the student. The left-hand side of Figure 1 summarizes user-adaptive and non-adaptive proactive features.

User-Adaptive Features. These features include making changes to the learning material (e.g., human circulatory system, algebra), conditions (e.g., time available), and assessments (e.g., quizzes), or the nature of ITS interactions with the learner (e.g., through a pedagogical agent; PA). These adaptive features can be better understood in the context of the information that drives them: *student models.* Student models are generated from data collected before the learning session that determines a student profile by identifying unique student characteristics or combinations of. Individual differences can include gender, psychological traits (e.g., personality traits), and prior knowledge of relevant content or skills that comprise an ITS' learning objectives [2]. This information can be used to adapt ITSs to learners even before a learning session,

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for example, by matching PA gender to learner gender and adapting instructional strategies to psychological traits.

Non-Adaptive Features. However, not all proactive features require adaptation to individual learners to effectively foster positive emotions. Non-adaptive features are characteristics strategically built into the design of an ITS with this goal in mind. These features focus on eliciting learners' engagement through features such as narrative (e.g., story-telling) and gamification. They can also support student autonomy (e.g., choice) by providing opportunities for learners to explore ITS content and features through hypermedia, rich 3D worlds, and customization. A recent review revealed that ITSs that used game-like features and afforded choice tended to elicit a greater proportion of positive emotions from students than those that did not [3].

1.2 Reactive Features

Although reactive features are adaptive in nature, the type of information they are programmed to respond to, as well as the nature of the response, can vary tremendously. At the broadest level, these features can be divided into two groups: *direct system prompts* and *CALM features* that refer to conditions, assessments, and learning material. The right-hand side of Figure 1 summaries the relationship between reactive features and the information they reply upon.

Dynamic User Models. The data that drives the reactive features stems from *dynamic user models* that include information collected on an ongoing basis about students' *psychological states* and *learning trajectories*. *Psychological state* information includes learners' concurrent state emotions (how they are feeling at the moment) and their attention to and engagement with the ITS. Collecting data at multiple intervals is critical because of potential changes in learners' emotions as a session progresses. Similarly, ITS student models can and should make use of formative assessments of students' evolving understanding (or lack thereof) as the session progresses and adapt accordingly. We refer to this data as information on students' *learning trajectory.*

CALM Reactive Features. These reactive features refer to non-prompt-based strategies for adapting ITSs to a learner's evolving psychological state and performance. They include adapting system conditions, assessments, and learning material. *Conditions* refer to the interaction parameters of an ITS, such as the degree of autonomy provided to students by the system (e.g., meaningful choice) and the availability of tools, such as embedded note-taking features. *Assessments* can be adapted to help up-regulate students' emotions in at least two ways. First, their administration can be altered to allow students more time to interact with content before being evaluated, or receive quizzes more regularly to maintain a more engaging learning pace and mitigate boredom. Assessments can also be made easier or more difficult to align with students' zone of proximal development (appropriately challenging items selected) and minimize feelings of frustration and hopelessness [4]. *Learning material* refers to the content or skills that an ITS is intended to facilitate (e.g., human biology, algebra). The difficulty of learning material can be adjusted by switching modules to more basic or advanced material or giving the learner an opportunity to take a break.

Direct System-Delivered Prompts. Most empirical work to date has examined the utility of system prompts provided to students through dialogue boxes or speech (using a text-to-speech engine), typically from an animated pedagogical agent [1,3,4,5]. Direct system-delivered prompts can target emotions either directly or indirectly depending on whether the aim is to change learners' *behavior* regarding their interaction with the system, or how the learner is *thinking*. We would classify a prompt recommending that a student return to task (e.g., off-task behavior) as a behavioral prompt because it is designed to change a student's emotional state by having them change their behavior. Most metacognitive and self-regulatory prompts are also behavioral at their core because of their explicit focus on scaffolding learners to engage in more effective learning behaviors. These effective learning behaviors help students regulate their emotions by targeting negative learning outcomes and situations that can elicit negative emotions. Such prompts may prevent negative situations from occurring, address the underlying problem, and/or influence appraisals of control.

The most popular and widely recognized emotional regulation strategies are those associated with cognitive change, and reappraisal in particular [4,5,6]. As such, prompts that target specific appraisals, such as learners' value of a task, self-efficacy, or locus of causality (i.e., control) are, in fact, more directly targeting how a learner *thinks (cognition)* as opposed to *feels (emotion)* about a task. Most of the motivational and emotion regulatory prompts tend to be targeting these processes, but are often referred to by different names (reactive empathy, general encouragement; [7]). Learners' emotions may also be regulated through social information such as *parallel empathy* which may be instilled through messages that direct learners' attention to the (alleged) feelings of a pedagogical agent who may also find an activity *boring* or *frustrating*. The underlying mechanism at work here is an appeal to the learner that their emotions are valid, but we would assert that the learner may positively modify one of their other appraisals as a result (e.g., self-efficacy or locus of causality).

Deployment of Direct System-Delivered Prompts. As with formative assessments and the administration of behavioral prompts, the frequency and timing of their administration are important considerations. The efficacy of direct system-delivered prompts thus depends, in part, on the source of the emotion information to which the system is programmed to react to. If the prompts are triggered in response to self-reported emotions, they then can only occur as often as the emotions are reported. If, however, the system is using continuous (online) data that is analyzed and processed in real time, more specific prompting decisions must be made such as: How often is too often to prompt students? Given these and other questions, there is one overarching guideline that can be safely heeded: Do no harm. More specifically, prompts need not be delivered if a learner is detected to be in a positive state.

1.3 Integrating Proactive and Reactive Features

Another important consideration in the deployment of prompts and other emotion-aware features is their combination. While some ITSs use more than one type of message in the prompts provided, no published work to date actively incorporates and evaluates the effectiveness of combinations of different proactive and reactive features (summarized in Figure 1). Given the preceding discussion, it is possible that this lack of knowledge may be addressed by integrating information about specific learners into user models. In this manner, it becomes possible to adapt system parameters before a learning session begins by augmenting the ITSs architecture with information concerning proactive features that, if administered, could positively affect engagement, positive emotions, and learning outcomes. Next, student models could be dynamically updated during the learning session with information on students' psychological states obtained from concurrent self-report measures of emotion or online methods such as physiological sensors or automatic facial expression recognition software. Reactive features such as system prompts, learning material, assessments, conditions (i.e., interaction parameters) can be adapted accordingly.

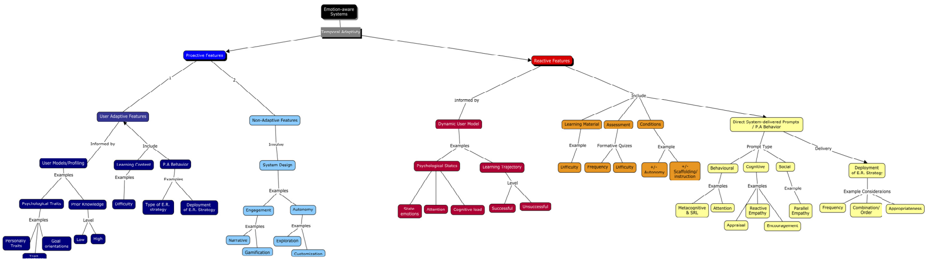

Fig. 1. Integrated Emotion-aware Frame Feature Map

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