

Three Research Directions for Affective Learning Technologies

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Abstract: Looking to the future of advanced learning technology research, understanding, supporting and explicitly designing for the role of affect is of great importance. I highlight three emerging areas of research with current research exemplars. First, simulating affect is necessary to enhance human-like relationships with technology; for example, with artificially intelligent virtual agents, or teachable robots as learning companions. Second, sensing and responding to learner affect in immersive learning experiences as well as learning at scale is rapidly evolving; for example, through affective intelligent tutoring systems, or dashboards driven by multimodal analytics. Third, designing technology-based learning experiences that promote, elicit and support affective outcomes requires theory building within the learning sciences; for example, to realize outcomes such as empathy or curiosity and formulate linkages to learning. Finally, I suggest how research in these areas of affective technology afford new opportunities to prepare learners for future learning and work environments.

Introduction

Perhaps the most uniquely human attribute in learning is the learner's emotion or affective state (emotions, feelings, moods) during the learning process. A recent review of cyberlearning research reported that the role of affect and emotion in the learning sciences is of much interest (Roschelle, Martin, Ahn & Schank, 2017). In general, we might expect that states such as engagement, flow and curiosity enhance learning while other states such as frustration and boredom inhibit learning, although research indicates this is more complicated. In the design of learning technologies, accounting for these affective states is an important area of interdisciplinary research that spans the fields of the learning and computer sciences, psychology, engineering, neuroscience, and other convergent fields such as affective computing and cyberpsychology.

Three research directions

In this crossover paper, I highlight three areas of research for affective learning technology: 1) Simulating affect to enhance the human-like aspects of the technology; 2) Sensing and responding to learner affect in immersive environments and nonformal settings; and, 3) Supporting affective learning-related outcomes.

Simulating affect to enhance human-like aspects of technology

Based on the Computers as Social Actors (CASA) paradigm (Reeves & Nass, 1998), there is much evidence to support that learners respond to technology as human-like, even if it is not conscious. For example, the politeness effect with virtual agents indicates that polite, socially intelligent, pedagogical agents can positively impact learning (Wang et al., 2008), and there is strong evidence that virtual agents can serve as effective social influencers (Baylor, 2011). For technology to provide affective and motivational support during learning, it is more effective if it engages with the learner socially and emotionally.

Walker and Ogan (2016) suggest that the artificial-intelligence in education (AIED) community should actively design such technology-mediated social relationships. Particularly for affect, we must design affective characteristics that not only enhance the human-technology relationship but also align with the desired instructional role of the technology (e.g., as expert, mentor, learning companion, or peer; Kim & Baylor, 2016). Ultimately, making the technology more human-like can improve learning, through mechanisms such as the use of enthusiasm, (Lane et al., 2013) or the design of systems that "care" (Du Boulay et al., 2010).

The design of affective characteristics may be clear and simple to provide a strong message, such as through the teachable robot "Quinn" that provides feedback to learners with facial emotions together with causal attributions regarding the learning process (Muldner, Girotto, Lozano, Burleson, & Walker, 2014). Or the affective characteristics may be more complex to generate rapport with both emotional expression and nonverbal communication. For example, an embodied conversational agent serving as a virtual peer has rapport with the learner to facilitate science achievement in a culturally diverse classroom (Finkelstein, Yarzebinski, Vaughn, Ogan, & Cassell, 2013).

Overall, simulating affect to support and not detract from learning will likely lead to more human-like systems that enhance learner engagement through human-technology partnerships. Particularly for intelligent systems, more work is also needed to determine how technology should emote more realistic affect to show intention and/or articulate what is in the simulated "black box."

Sensing and responding to learner affect in both immersive environments and larger-scale nonformal settings

Moving from the technology to the learner, how can advanced learning technologies sense and respond to learners' affective states and the combination of affect and cognition that occurs in learning? We need to better understand this within immersive learning experiences as well as more distant learning contexts such as MOOCs. A recent 2017 inaugural summit on Emotion AI (see <http://go.affective.com/emotion-ai-summit>) suggests the importance of designing such systems not only from the perspective of academia, but also industry.

Arroyo and others (2009) described how “emotion sensors go to school” as integrated in an affective intelligent tutoring system. Continuing to the present day, the implementation of affect-aware systems is rapidly evolving. For example, the game-based learning environment Crystal Island serves as a platform to investigate how emotional responses, such as feelings of calm or tension, are involved in learning for middle grade science and literacy (Sabourin, Mott, & Lester, 2011). Incorporating advances from the affective neurosciences, the Affective Autotutor responds to student affective states including boredom, confusion and frustration (Immordino-Yang & Singh, 2011). For learning at scale, detecting learner engagement in MOOCs is important to support student success. While self-reported affect data can be collected as a first step (Dillon et al., 2016), such systems are now starting to incorporate more intelligent affect-aware feedback (Grawemeyer et al., 2016).

An interesting angle is the development of dashboards to provide “super-senses” for instructors to assess students' cognition, metacognition, emotion, and motivation using multimodal data. These dashboards can incorporate information from eye gaze behaviors, facial expressions of emotions, heart rate, and electrodermal activity (Azevedo et al., 2017). A major challenge here is how to integrate multimodal information that may include multichannel physiological signals. More systematic research on interface design for these dashboards is also needed to make them usable for teachers or other leaders. Importantly, as we continue to build such systems and integrate technologies such as detecting emotion through facial recognition, careful consideration must also be made to ethical issues including privacy.

In this research area, more research is needed to better integrate multimodal data with other techniques such as natural language processing. Developing these affect-aware learning technologies requires advances in computer science and engineering in particular, an area referred to as *affective computing*, per Picard's classic book (1995).

Supporting affective learning-related outcomes

Finally, we need research on the design of learning experiences to promote and support desirable affective outcomes and related motivational constructs such as engagement, interest and curiosity. We also need theory-building in the learning sciences to understand these technology-mediated cognitive-affective states and make the connections back to learning. For example, Leutner (2014) presents the Cognitive-Affective Theory of Learning with Media (CATLM) as an extension of Mayer's Cognitive Theory of Multimedia Learning, which suggests how affective features of instruction can increase learner engagement, generative processing, and deeper learning. D'Mello and Graesser (2012) propose a model that describes the role of cognitive disequilibrium and its dynamic relationship to learners' affective states; specifically, that if such cognitive challenges are resolved, the learners will return to a state of engagement/flow, but if not, can trigger frustration and ultimately boredom. To support and understand affective learning outcomes in nonformal settings like MOOCs, much more research is needed, and in particular, there is a need for more experimental approaches as noted in a recent review article (Joksimović et al., 2017).

What affective states should we promote and support and what are the unique affordances of technology? Immersive virtual reality (VR) environments are particularly powerful in the capacity to induce distinct affective states such as joy, sadness, boredom, anger or anxiety (Felnhofer et al., 2015), and there are ethical concerns given that simply acting as an avatar in VR, for example, can serve as an emotionally-intensive experience and have unintended impact. On the positive side, perspective-taking as implemented through technology can serve as an effective way to promote empathy. Ben Shapiro's initial work (<https://www.colorado.edu/atlas/pet-project>) involves students designing wearable technology that allow them to sense the world through the eyes of a pet; for example, they create earmuffs that allow for the frequencies that dogs hear, and augmented reality lenses that simulates dog vision. Through this perspective-taking, students develop empathy for the pet and this in turn facilitates their curiosity to ask scientific questions and enhance their overall interest in the scientific process. Accordingly, curiosity is a valuable outcome in relation to STEM learning, and there is much recent interest (e.g., a recent ACM SIG CHI 2016 workshop) in designing systems to support it and the closely related concepts of serendipity, interest, intrinsic motivation and goal-setting, and creativity.

Research in this area should advance our understanding of which affective learning outcomes to target and the implications for the design of learning technologies. If we were to explicitly design systems to elicit feelings of delight and surprise (which Baker and colleagues found to be rare (2010)) and even those of awe and wonder, the possibilities for enhancing interest in content such as STEM could be profound.

Conclusions and implications

Table 1 below provides a summary of these three research areas (e.g., simulating, sensing, and supporting learning affect), exemplars reflecting the current state, and future directions.

Table 1: Affective learning technology research: State-of-the-art and future directions

Research area	Current state-of-the-art	Future directions
Human-like technology (<i>Simulating</i> affect)	artificially intelligent virtual agents; social robots	Increasing realism, rapport, and social responsiveness; systems emoting to inform learner of intention and generating interest and buy-in
Affect-aware systems (<i>Sensing</i> learner affect)	affective intelligent tutoring systems; dashboards with multimodal data; MOOCs that assess learner engagement	Generating more meaningful learning-related information from multi-channel multimodal data; role of emotion AI and learning; more sensitive detection and modeling of learner affect for learning at scale
Affective learning outcomes (<i>Supporting</i> learner affect)	Support flow/engagement; cognitive disequilibrium as integral to the learning process	Discovering new strategies to elicit emotions such as empathy, delight, curiosity; modeling the complex relationship with learning and cognition; deeper investigation of the affordances VR

As we prepare learners for the future of work, the role of affect is fundamental for both designing and working within immersive and intelligent environments where technology can understand and use emotion in its partnership with the learner or worker. Such cyber-human systems of the future must both understand, respond to and communicate with gesture, emotional expressions and nonverbal behaviors.

Each of these three directions requires a highly interdisciplinary, or convergent, approach to understand the theoretical and empirical underpinnings of affective learning technologies. This can be problematic in evaluating impact- i.e., which field gets to determine the parameters for evaluation? Here it is important to broaden the scope of relevant research, and bring flexible, multi-dimensional evaluation lenses to bear in support of these exciting new directions.

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Acknowledgments

This material is based upon work supported by (while serving at) the National Science Foundation. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.