Personalization of AI-Supported Ecological Learning: Affective Experiences as a Function of Traits, Beliefs, and Behaviors

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Abstract

Artificial intelligence (AI) is increasingly applied in educational contexts to enhance learning experiences, including affect. The current study uses 1) self-report data on achievement traits and learning-related beliefs and 2) behavioral data from an AI-based modeling tutor to investigate correlates of widely studied achievement emotions. Trait data was largely unrelated to affect, apart from a negative relationship between trait anxiety and the frequency of self-reported surprise during the learning episode. Positive beliefs were correlated with reduced negative affect, but not increased positive affect. Model complexity was positively correlated with surprise and excitement. Theoretical (understanding affective processes in AI-supported learning) and practical (designing feedback to promote positive affect) implications are discussed.

Theoretical Background and Objectives

As AI learning agents proliferate in educational settings, additional attention must be paid to learners' affective experiences. Although historically the study of technology-mediated learning has focused on 'cold' cognitive processes, recent perspectives advocate for a more holistic investigation of learner experiences, centering emotions as the "experiential glue" (Graesser, 2020) of 21st century learning. Affect contributes not only to positive achievement outcomes, but also to sustained cognitive and motivational engagement (Pekrun & Linnenbrink-Garcia, 2012).

'Learner models' (i.e., representations of what a learner knows and can do; Luckin et al., 2016) guide AI-based personalization of learning experiences. However, these in-situ methods provide reactive (versus proactive) personalization, and those developed for affect management require conversational or physiological data to estimate emotions experienced by the learner (e.g., D'Mello & Graesser, 2010; 2013). The current study describes relationships between learning-related emotions (Pekrun et al., 2017) and a battery of self-report and behavioral measures collected before and during interaction with an AI-based modeling tutor.

The traits included in the current study are mastery, anxiety, and persistence. Individuals high in Mastery (Heggestad & Kanfer, 2000) strive for achievement, defined by exceeding personal task mastery standards. Mastery-oriented goal adoption is in turn associated with positively valenced emotions and lower frequency of negatively valenced emotions (Pekrun et al., 2009). Trait persistence refers to a general tendency to maintain goal-directed action despite challenges (Cloninger et al., 1993). Although often studied in learning contexts as an outcome of emotions (e.g. Tulis & Fulmer, 2013), persistence behaviors and emotion may have a reciprocal relationship (Li & Lerner, 2013; Skinner et al., 2008). In contrast to mastery and persistence, trait anxiety in achievement contexts represents stable tendencies oriented towards failure avoidance (Heggestad & Kanfer, 2000). Although anxiety is commonly treated as a state, trait conceptualizations also contribute to achievement emotions (Nett et al., 2017).

Beliefs are a more proximal influence on affective processes, and common theoretical approaches delineate learning beliefs in terms of expectancy (or control) and value (Eccles & Wigfield, 2002; Pekrun, 2006). Self-efficacy beliefs indicate a learner's perceived ability to engage in behaviors associated with task success (Bandura, 1997) and are an antecedent of experienced emotions (Pekrun, 2006). Process expectancy beliefs (Doménech-Betoret et al., 2017) assess expected feelings during learning, and in the current study refer to learners' anticipated frustration. In part, value beliefs refer to learners' perceptions of the learning activity's utility (i.e., usefulness; Wigfield & Eccles, 2000), assessed in the current study by anticipated helpfulness of the AI tool for learning.

Finally, we draw from prior research on in-situ detection of learner affect to explore correlations between behavioral trace data and achievement emotions. Affective-sensitive intelligent tutors have previously detected learner affect based on conversational and visual (e.g, body language, facial movement) cues (D'Mello & Graesser, 2010; 2012; Nye et al., 2014). In the current study, we hope to explore how affect might be detected in-situ in a context without access to conversational cues or physiological measures. We posited that person-centric interpretations of learners' interactions with AI learning technologies could help 1) anticipate patterns of affective experience during learning and 2) inform design of feedback mechanisms or other pedagogical interventions for AI technologies that do not collect multimodal learner data. Specifically, we asked:

In the context of an AI based learning experience...

1. *How are achievement traits related to affect experienced during learning?*
2. *How are learning-related beliefs related to affect experienced during learning?*
3. *How are modeling behaviors related to affect experienced during learning?*

Method

Participants

Participants were students (N = 68) enrolled in a Masters-level cognitive science course at a large Southeastern university. Demographic characteristics of the sample are provided in Table 1. Prior to enrolling, less than 12% of the sample (N = 8) had heard of the AI learning agent used in the study, and none had used it.

Materials and Measures

AI-Based Learning Agent: The Virtual Ecological Research Assistant (VERA)

VERA allows users to evaluate and revise hypotheses about ecological systems by creating and simulating ecological models (An et al., 2020; 2022). Users build models containing components classed as biotic (e.g., a species population), abiotic (e.g., sunlight), or habitat (areas where biotic/abiotic components can reside/migrate); they can also specify relationships between components. For each component they can modify parameters. After users have developed hypotheses and constructed models, an AI-based compiler simulates the phenomena (i.e., shows population changes over time) using only the drag-and-drop tools – no programming skills are required. Learners use the results of the simulation to inform future hypotheses/models.

Achievement-Related Traits

See Table 2 for descriptive statistics. All trait measures used a six-point scale ranging from “Very untrue of me” to “Very true of me”.

Mastery. Mastery was assessed using items from the short-form version of the Mastery scale within Kanfer and Ackerman's (2000) Motivational Trait Questionnaire. An example item is "I set high standards for myself and work toward achieving them".

Anxiety. Trait anxiety was assessed using three items from the International Personality Item Pool (IPIP; Goldberg et al., 2006), adapted for learning-related situations. An example item is "I get stressed out easily when learning something new".

Persistence. Trait persistence was assessed using five items from the IPIP representation of Peterson & Seligman's (2003) persistence scale. An example item is "I don't quit a task before it is finished".

Learning-Related Beliefs

Learners' beliefs about future interactions with VERA were assessed using three items, each on a six-point scale ranging from "Strongly disagree" to "Strongly agree". See Table 2 for descriptives.

Expected Helpfulness. The extent to which VERA was expected to be helpful was assessed with the item "VERA will be helpful to my learning".

Expected Frustration. The extent to which VERA was expected to be frustrating was assessed with the item "Using VERA will be a frustrating experience".

Self-Efficacy. The extent to which users felt efficacious in their use of VERA was assessed on a scale with the item "I am confident in my ability to use VERA".

Affect

Participants' affect was assessed using the short form of the Epistemically-Related Emotion Scales (EES; Pekrun et al., 2017) on a six-point frequency scale (Never – Very frequently).

VERA Data

Several aspects of participants' VERA interactions were extracted, including 1) number of models created, 2) time spent per model, and 3) average model complexity (i.e., total number of components and relationships within a model).

Procedure

Data was collected over the course of the Spring 2023 semester. In the first week, participants completed survey measures capturing achievement-related traits and learning-related beliefs. The VERA activities were assigned in the sixth week of the course, and the affect scale was administered following the VERA course assignment. Although all students were required to interact with VERA as part of the course activities, log data was only retained for students who provided consent to use their VERA models for research purposes (N = 55).

Results

Research Question 1: Achievement Trait–Affect Relationships

Achievement traits did not show consistent patterns of relationships with learning-related emotions (see Table 3). Mastery in particular was generally unrelated to affect. Anxiety and persistence had somewhat more interesting patterns of relationships emerge. Anxiety showed small negative relationships with frequency of two positively valenced emotions (r_{surprise} = -0.269; $r_{\text{excitement}}$ = -0.226), while persistence showed small negative relationships with frequency of two negatively valenced emotions ($r_{\text{frustration}}$ = -0.235; $r_{\text{confusion}}$ = -0.225) and a small positive relationship with excitement (r = 0.239.) Although of these only the relationship between trait anxiety and state surprise was statistically significant, power may have been limited due to the size of the course.

Research Question 2: Learning Belief–Affect Relationships

Relative to the traits assessed above, learners' beliefs showed more consistent patterns of correlations with affect (see Table 4). Self-efficacy for using VERA showed small to moderate correlations with all surveyed emotions except for curiosity, surprise, and excitement. Expected helpfulness of the AI tool showed moderate negative correlations with several negatively valenced emotions (r_{anxiety} = -0.303; $r_{\text{frustration}}$ = -0.305; $r_{\text{confusion}}$ = -0.381). Unexpectedly, confusion was the only emotion significantly related to expected frustration (r = 0.362).

Research Question 3: Behavior–Affect Relationships

Total models created and average time spent per model were not significantly related to self-reported affect. Interestingly, however, there were significant relationships between average model complexity and self-reported surprise (r = 0.467) as well as excitement (r = 0.296) (i.e., students who created more complex models on average reported more frequent surprise and excitement). See Table 5 for all behavior-affect relationships.

Discussion

Summary and Theoretical Implications

The primary aim of the current study was to assess the patterns of relationships between learners' emotions during use of an AI tool and 1) more distal achievement traits, 2) learning-related beliefs, and 3) modeling behaviors. Consistent with prior literature on antecedents of learning-related emotions (Eccles & Wigfield, 2002; Pekrun, 2006), beliefs showed generally consistent patterns of relationships with affect while achievement traits were largely unrelated. Although these traits may be too distal to be directly informative of affective experiences with AI learning tools, they were related to participants' learning related attitudes ($r_{exp.\ helpfulness,\ mastery}$ = 0.360; $r_{exp.\ helpfulness,\ anxiety}$ = -0.456; $r_{exp.\ helpfulness,\ persistence}$ = 0.513; $r_{exp.\ frustration,\ anxiety}$ = 0.287; $r_{self\text{-}}$

$_{efficacy, anxiety}$ = -0.410; $r_{self\text{-}efficacy, persistence}$ = 0.378) which is consistent with prior research on the relationship between traits and task appraisals (Hemenover & Dienstbier, 1996).

Some of our results regarding learning beliefs are consistent with widely studied relationships between motivational beliefs (e.g, self-efficacy) and emotions (e.g., Acee et al. 2010). For example, self-efficacy was negatively correlated with negative affect (e.g., state anxiety, frustration). Notably, however, other beliefs in several cases did not always show the expected affective relationships. Expectations of frustration, for example, did not show a significant relationship with frequency of (state) anxiety or frustration. This suggests that learners' expectations of AI-supported learning experiences may be somewhat inaccurate, perhaps because they are less likely to have previously encountered a similar task. Future studies, therefore, might examine when/why students' appraisals of AI-supported learning tasks are (in)accurate.

Practical Implications

In pedagogical settings, positive learning experiences are likely to result in improved motivational (i.e., self-efficacy) or performance outcomes. In terms of affect, these positive experiences might be characterized either by the absence of negative emotions (which inhibit desired outcomes) or the presence of positive emotions (which promote desired outcomes). Our results suggest that instructors might promote the former by providing students with scaffolded learning experiences intended to increase self-efficacy before engaging with an AI tool, perhaps reducing the occurrence of emotions such as frustration. Likewise, the latter might be facilitated by directing students toward specific in-system behaviors (e.g., emphasizing model complexity) that have been found to promote emotions like surprise and excitement. In situations such as online or asynchronous contexts, equivalent learner support might be provided by personalized feedback mechanisms. The design of feedback mechanisms informed by psychological theory is one of several ongoing projects currently underway for VERA.

Conclusion

Affect detection in intelligent tutoring contexts often relies on physiological or facial recognition methodologies. Given that these may not be available in classroom contexts, we investigated the relationship between affect and several sets of measures, including distal (i.e., achievement-related traits) and proximal (i.e., learning-related beliefs) survey measures as well as trace data from the intelligent tutor. While more distal measures were generally unrelated to affect, we found interesting patterns of relationships between learning-related beliefs and negative affect, as well as between trace data and positive affect. These results may help inform understanding of affect in AI-supported learning contexts, and facilitate classroom use of AI technology in ways that promote positive affect.

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Table 1. Sample Descriptives.

	Female	**Male**	**Total**
18-24	24	24	48
25-34	7	10	17
Total	31	34	65

Note. 3 participants did not provide demographic information.

Table 2. Descriptive Statistics for Survey Measures.

	N	*M*	*SD*	α
Achievement Traits				
Mastery	67	4.91	0.68	0.68
Anxiety	67	3.38	0.89	0.56
Persistence	67	4.47	0.67	0.58
Learning-Related Beliefs				
Expected Helpfulness	59	4.51	0.82	-
Expected Frustration	63	2.81	1.03	-
Self-Efficacy	64	3.95	1.35	-
Affect				
Boredom	64	3.11	1.39	-
Anxiety	64	1.95	1.17	-
Frustration	64	2.59	1.35	-
Confusion	64	3.12	1.27	-
Curiosity	64	4.19	1.05	-
Surprise	64	3.47	1.28	-
Excitement	64	3.59	1.41	-

Table 3. Correlations between achievement traits and affect.

	Mastery	**Anxiety**	**Persistence**
Boredom	0.122	0.122	-0.052
Anxiety (state)	0.169	-0.063	0.011
Frustration	0.080	0.144	-0.235
Confusion	0.087	0.173	-0.225
Curiosity	0.009	0.007	-0.015
Surprise	0.052	-0.269*	0.074
Excitement	0.159	-0.226	0.239

Note. N = 63; * indicates $p < 0.05$

Table 4. Correlations between learning-related beliefs and affect.

	Expected Helpfulness	**Expected Frustration**	**Self-Efficacy**
Boredom	-0.183	0.187	-0.262*
Anxiety (state)	-0.303*	0.174	-0.257*
Frustration	-0.305*	0.176	-0.273*
Confusion	-0.381*	0.362*	-0.468*
Curiosity	-0.062	0.137	0.026
Surprise	-0.007	0.126	0.085
Excitement	0.086	-0.012	0.215

Note. N = 55-60 (variations in pairwise missing data); * indicates $p < 0.05$

Table 5. Correlations between VERA behaviors and affect.

	Models Created	**Avg. Time Per Model**	**Avg. Model Complexity**
Boredom	-0.025	0.074	-0.171
Anxiety (state)	-0.109	-0.112	0.010
Frustration	0.165	-0.258	0.175
Confusion	-0.136	0.107	0.116
Curiosity	-0.094	-0.0232	0.269
Surprise	-0.151	-0.056	0.467*
Excitement	0.033	-0.142	0.296*

Note. N = 53-54 (variations in pairwise missing data); * indicates $p < 0.05$