Dynamics of Affective States During MOOC Learning

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Abstract. We investigate the temporal dynamics of learners' affective states (e.g., *engagement, boredom, confusion, frustration*, etc.) during video-based learning sessions in Massive Open Online Courses (MOOCs) in a 22-participant user study. We also show the feasibility of predicting learners' *moment-to-moment* affective states via implicit photoplethysmography (PPG) sensing on unmodified smartphones.

Keywords: Massive Open Online Courses · Intelligent Tutoring Systems · Physiological signals · Affective computing

1 Introduction

Learning is an affectively charged experience. Previous studies have shown that learners experience a rich diversity of affective states, including *engagement*, *boredom*, *confusion*, *curiosity*, *happiness*, and *frustration* in the process of learning. Affective states can significantly influence learners' motivations, behaviors, and even learning outcomes [3]. Researchers have conducted systematic studies to understand [2], detect [3, 6], and adapt to [5] learners' affective and cognitive states in computer-mediated learning systems. Both the occurrence of learning-centered affective states and the dynamic temporal transitions between them [2] have been studied in complex learning environments, i.e., solving multi-step, time-consuming questions. Nevertheless, little work has been done to understand the dynamics of affect in Massive Open Online Courses (MOOCs) to date. Different from the *interactive* experiences in Intelligent Tutoring Systems (ITS), students in MOOCs learn primarily via *passive* video-watching. As a result, many findings in the complex learning domain might not be applicable to MOOC learning.

In this paper, we investigate the temporal dynamics of learners' affective states during short video-based MOOC learning sessions. Through a 22-participant user study, we quantify both the frequency of occurrence and the dynamic transitions of common affective states during MOOC learning. This work extends the model of affect dynamics in complex learning proposed by D'Mello et al. [2] to MOOC contexts. Moreover, we explore the feasibility of predicting a learner's *moment-to-moment* affective states by analyzing her PPG signals implicitly captured by the built-in camera of smartphones during MOOC learning.

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2 Methodology

Twenty-two college students (10 females) participated in our study to investigate the dynamics of affective states in video-based MOOC learning sessions. Participants took a mini MOOC course (the introductory section of the Coursera course “Cryptography”) with three lecture videos (30 min in total). To collect learners’ moment-to-moment affective states during learning, we asked participants to provide judgment of their affective states at fixed affect judgment points in the video when the video paused automatically. Affect judgment points were either at the end of each concept or after the instructor asked a question and sought answers from the audience. The intervals between two consecutive judgment points ranged from 21 s to 80 s (average 42 s). There were 47 affect judgment points in total across the whole lecture. At each affect judgment point, participants were provided with a checklist of nine states (*engagement, boredom, confusion, frustration, surprise, delight, curiosity, happiness,* and *neutral*) to mark along with definitions of each state. These states were reported to occur during learning with technology [2, 3]. Participants were also asked to rate the level of valence (displeasure to pleasure) and arousal (deactivation to activation) they experienced using the Self-Assessment Manikin’s (SAM) [1].

While participants were watching the lecture videos, we also recorded their PPG signals using the LivePulse [4] application running on a Nexus 5 smartphone.

3 Result

3.1 Affective States in MOOCs

A total of 1034 self-reported affect judgments were collected from the 22 participants. There were 35.7% instances of *engagement*, 13.2% *boredom*, 14.5% *confusion*, 2.3% *frustration*, 1.6% *delight*, 2.0% *surprise*, 11.8% *curiosity*, 3.4% *happiness*, and 15.6% *neutral*. A repeated measures ANOVA on the distribution of affective states indicated a statistically significant difference, $F(8, 168) = 21.8$, $p < 0.0001$. *Engagement* was the most frequent affect, followed by *boredom*, *confusion*, *curiosity*, and *neutral*. Unlike complex learning, *frustration* had low frequency during the MOOC learning session. There were also only a few occurrences of *delight*, *surprise*, and *happiness.*

To identify the frequently occurring transitions between affective states, we used the transition likelihood metric L in [2] to compute the likelihood of transitions from one state to another state. Our investigations focused on the frequently occurring states (*engagement*, *boredom*, *confusion*, *curiosity*, and *neutral*) and *frustration*, a primary negative affect in learning [2, 3]. To determine the significance of transitions between two affective states, we first calculated the transition likelihood for each transition per participant. Then, we used one-sample t-tests to check the significance of the transitions. Figure 1 presents the descriptive statistics for the likelihood that each of the 6 investigated affective states immediately follows another.

Different from the affect dynamics in complex learning [2], we observed that the *engagement→boredom* transition was significant. This finding suggests that learners in MOOC contexts are more likely to enter *boredom* than they are in complex learning.

Moreover, we did not observe a strong *confusion* → *engagement* transition as in complex learning [2]. Based on participants' subjective feedback, the occurrences of *confusion→engagement* in MOOCs depend more upon the content and flow of the video than upon the learners actively figuring out the problem themselves (as in complex learning). Because of this large reliance on the content and flow of the video, learners tend to remain confused if their questions or doubts are not answered in the video.

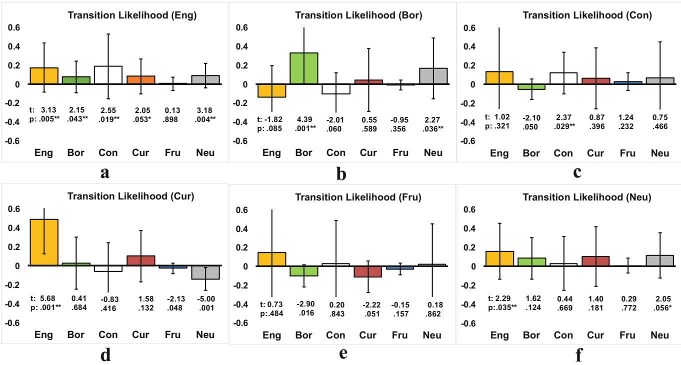

Fig. 1. The likelihoods that each state immediately follows (a) *engagement* (b) *boredom* (c) *confusion* (d) *curiosity* (e) *frustration* (f) *neutral*.

3.2 PPG Signals and Moment-to-Moment Affective States

With the data collected in the study, we also investigated the feasibility of detecting learners' moment-to-moment affective states using the PPG signals collected by the built-in camera of smartphones. For each subject[1], we extracted heart rate variability (HRV) [6] features from the PPG signal segment right before each affect judgment point, and used these features to predict the learner's affective state at that judgment point. To have a long enough PPG sequence to make an accurate prediction and reduce the carry-over effect, we removed those affect judgment points which were too close to the previous affect judgment point (interval < 30 s), leading to a total of 33 affect judgment points per participant. We used LivePulse algorithm [4] to extract RR-intervals from each PPG signal segment. 11 dimensions of HRV features were then calculated based on these RR-intervals: (1) AVNN; (2) SDNN; (3) rMSSD; (4–7) pNN5, pNN10, pNN20, pNN50; (8) MAD; (9) SDANN; (10) SDNNIDX; and (11) rMSSD/SDNNIDX. Definitions of these features can be found in [5, 6]. For each participant, all features were rescaled to [0, 1].

Using self-reported affect judgments as the gold standard, we performed the following detection tasks: (1) detecting whether the learner is in an *engagement*, *boredom*, or *confusion* state (yes or no, binary classification); (2) detecting whether the learner is

[1] We removed data from S1 and S4 in this analysis because the PPG data collected from these two subjects were incomplete.

in a negative state (low valance); and (3) detecting the occurrence of critical events which are marked by strong emotions (high arousal values). We used the Support Vector Machine (SVM) with a radial basis function (RBF) kernel to build the classifiers. We built both user-independent models and user-dependent models. The user-independent models were built using the data from all subjects and were evaluated via leave-one-subject-out evaluation. User-dependent models were built for each participant individually and evaluated with 10-fold cross-validations. Table 1 lists Kappa's best performance for each classification task. The Kappa score indicated a clear relationship between learners' affective states and their PPG signals.

Table 1. The performance of different moment-to-moment affective state prediction tasks

Detection	*User-independent*		*User dependent*	
	Accuracy	Kappa	Accuracy	Kappa
Engagement	70.8%	0.151	62.0%	0.277
Boredom	83.6%	0.077	83.7%	0.139
Confusion	80.1%	0.070	83.7%	0.205
Negative events (low valence)	85.5%	0.107	85.0%	0.182
Critical events (high arousal)	84.8%	0.233	84.6%	0.285

4 Conclusion

This paper presents a 22-subject study to understand the dynamic transitions of affective states during video-based MOOC learning. We also show the feasibility of using implicit PPG sensing to detect moment-to-moment affective states. This research is an initial step towards a holistic understanding of learners' affective states during typical video-based MOOC learning sessions.

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