Student Emotion, Co-occurrence, and Dropout in a MOOC Context

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ABSTRACT
This paper discusses self-reported emotions experienced by students in a Massive Open Online Course (MOOC) learning context. Emotions have been previously shown to be related to learning in classrooms and laboratory studies and have even been leveraged to improve learning. In this study, frequently occurring discrete emotions as well as frequently, co-occurring pairs of emotions were analyzed during learning with a MOOC. Both discrete and co-occurring emotions were related to students dropping out of the course, illustrating the importance of student emotion in a MOOC context.

Keywords
MOOC; affective computing; course completion.

1. INTRODUCTION
Emotion is one of the key aspects of the learning process [9,22]. It influences learning in a variety of ways [12], both positively (e.g., when a student feels engaged [19]) and negatively (e.g., during boredom [6,19]). These connections between emotion and cognition can be leveraged to improve learning [10]. For example, a dialog-based, intelligent tutor that adjusts its dialog to address negative emotions can improve learning for low-knowledge students [11]. Indeed, the relationship between emotion and learning has been researched in a variety of digital learning contexts in both laboratory studies and classroom studies [1,5,9]. There are, however, additional learning contexts in which the relationship between emotion and learning is less clear. In this study we focus on the role of emotion as it relates to student dropout in the context of a Massive Open Online Course (MOOC).

MOOCs are an online learning context that has recently become popular worldwide [18]. MOOCs provide education access to large groups of people, many of whom are often non-traditional students. Little is known about the relationship between emotions and learning in a MOOC context. Some initial work toward examining emotion in MOOCs indicated that some emotions were related to dropout [13]. However, these results were derived from retrospective reports of emotion after a course rather than reports in the moment, i.e., *during* the course. Similarly, studies have used MOOC discussion forums and clickstream data to infer student emotions such as *Confusion* and *Frustration* based on researchers' judgments of how these emotions are manifested [16,27], but there was no measurement of the emotions from the students themselves.

The current paper expands on this limited research, addressing key open questions about student emotions gathered from self-reports at different points in a MOOC. We explore a range of emotions, including *Anger*, *Boredom*, *Confusion*, *Contentment*, *Disappointment*, *Enjoyment*, *Frustration*, *Hope*, *Hopelessness*, *Isolation*, *Pride*, *Relief*, *Sadness*, and *Shame*, while also focusing on the relationship between *Anxiety* and learning statistics (the focus of the MOOC in this study) [8,17].

We also consider the possibility of co-occurring emotions. Decades ago, Izard et al. [14] considered the possibility that certain emotions may be experienced in concert with other emotions, rather than individually. Experimental research has shown this to be the case in some situations, for example with induced emotions and even with emotions experienced during everyday life [3,21]. In the context of learning, Bosch and D'Mello [4] studied novice programmers' emotions and found confusion co-occurred with frustration, while curiosity co-occurred with engagement. The degree of co-occurrence of curiosity and engagement was positively correlated with learning (r = .226) after accounting for individual occurrences, thereby highlighting the importance of examining co-occurring emotions.

In addition to tracking the incidence of emotions and co-occurrence pairs, we also consider how emotions are related to key educational outcomes. Early studies of MOOC data and student behavior [7,26], have often focused on "dropout" as both a problem and a key outcome. Recently, some have questioned the validity of dropout as a metric of outcome assessment [13]. However, Yang et al. [26] have noted, for instance, that the average completion rate of a MOOC is 6.5%, which might signal some concern. Researchers have used log data to predict student dropout [15,23] as part of a larger effort aimed at better understanding student dropout from MOOCs and, in turn, improving the MOOC learning experience to reduce dropout. Here, we consider the relationship between students' self-reported emotions and course dropout.

To our knowledge, this is the first study to measure a range of student emotions in a MOOC context. We believe that the opportunity to study student emotion with large courses in the wild offers a valuable addition to previous work that has focused more on laboratory settings or traditional classroom environments. We address three related questions in this research:

- Q1. What emotions do students experience in a MOOC?
- Q2. Which emotion pairs co-occur more than chance?
- Q3. How do individual and co-occurring emotions relate to dropout?

2. METHOD AND COURSE SETUP

"I Heart Stats" was an introductory Statistics MOOC offered by a university in the Midwestern United States. One goal of the course was to alleviate student anxiety towards statistics. In this regard it was a prime opportunity to analyze student affect in a MOOC setting, while also providing an opportunity to study student affect at scale in the wild.

This MOOC contained eight modules covering topics ranging from levels of measurement to ANOVA. Modules were designed to be completed in sequential order. Nevertheless, all modules were released to students at the same time, so students were free to complete the modules at their own pace and in whatever order they desired.

We used a "Pick-Two" list of 15 discrete emotions (Figure 1) to measure student affect. In addition to the typical set of learning-centered affective states like *Confusion* and *Boredom* [9], the list included several additional emotions, such as *Enjoyment*, *Pride*, *Isolation*, *Hope*, and *Shame*. These emotions were, in part, selected from Pekrun's description of academic emotions [20]. One limitation of this emotion list was that *Neutral* was not included. Students were prompted to report emotions at the start of even-numbered modules (0, 2, 4, 6) as well as at the end of module 8 (last module). We only collected affect reports on every other module to minimize intrusion.

Of the 24,279 students from 183 different countries enrolled in the course, 3,591 students reported exactly two emotions on at least one module. These 3,591 students constituted the sample in this study. Students were able to report greater or fewer than two emotions, but because we were interested in co-occurrence, we excluded responses that did not consist of exactly two emotions.

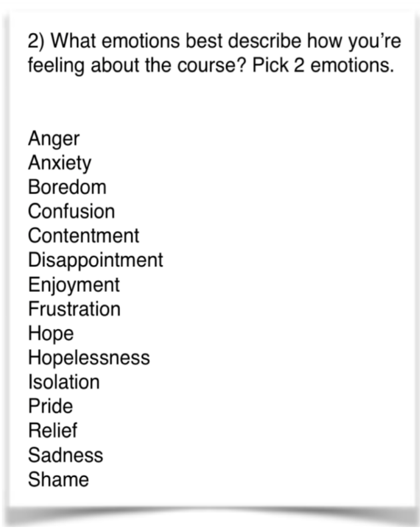

Figure 1. Screenshot of the emotion reporting interface

In addition to five "course-level" affect surveys, in which students reported their emotions in relation to the course as a whole, we also included seven "content-level" surveys. These content-level surveys were spread throughout the course and prompted students to report their emotions in response to different video lectures and problem sets. These are two common content-delivery methods for MOOCs, thereby providing a preliminary understanding of student affect when completing these two activities.

3. RESULTS

We used both the course-level and content-level students self-reported emotions to answer our research questions (see Introduction).

Q1. What emotions do students experience in a MOOC?

Figure 2 presents the aggregated proportions of each reported emotion across all five course-level surveys. We note that *Hope* and *Enjoyment* were the most frequently reported emotions. Other frequently reported emotions were *Contentment, Anxiety,* and *Pride,* while *Shame, Disappointment, Isolation, Anger*, and *Sadness* were rarely reported.

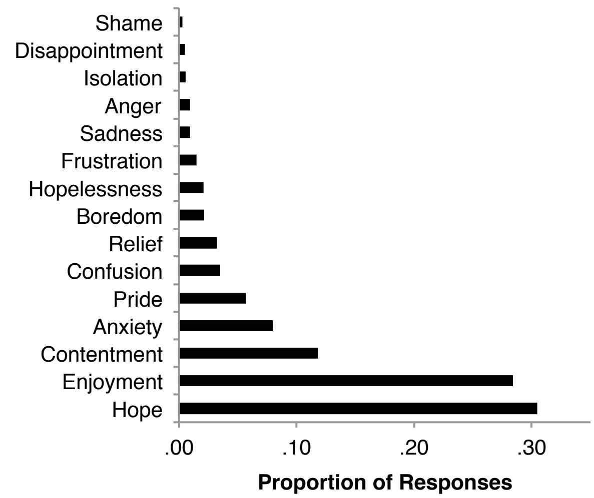

Figure 2. Proportions of self-reported emotions

These results differ from the recent D'Mello meta-analysis [9], where the studies rarely included emotions such as *Hope*, *Enjoyment*, and *Contentment.* However, the focus there was on short one-on-one interactions during learning with technology. A different set of emotions appear to be playing a critical role in the MOOC context, so context clearly matters. It is, however, difficult to separate context differences from measurement differences in the present study.

In addition to the course-level emotion surveys, we also included the content-level affect surveys to assess self-reported emotion in relation to specific segments of content that may elicit different emotional responses. We selected 4 content-level affect surveys to highlight different affective states across video and problem set sections of content. Two of the activities were short instruction videos and the other two were homework and practice problem sets. We excluded emotions that occurred in less than 1% of the responses for each specific activity. In addition, since all of the content for this course was released at the same time, we use log timestamps to ensure that: 1) Students engaged with the activity, 2) Students answered the activity-specific affect question *after* their engagement with the activity, and 3) Students did not take more than 1 hour following the last activity log to complete the emotion survey.

Figure 3 presents the emotion proportion distributions for four learning activities. The results indicated that unlike the course-level emotion reports, *Enjoyment* was more frequent than *Hope*. Further, while *Anxiety* was the fourth most commonly reported emotion at a course-level, it was far less prominent at the content level.

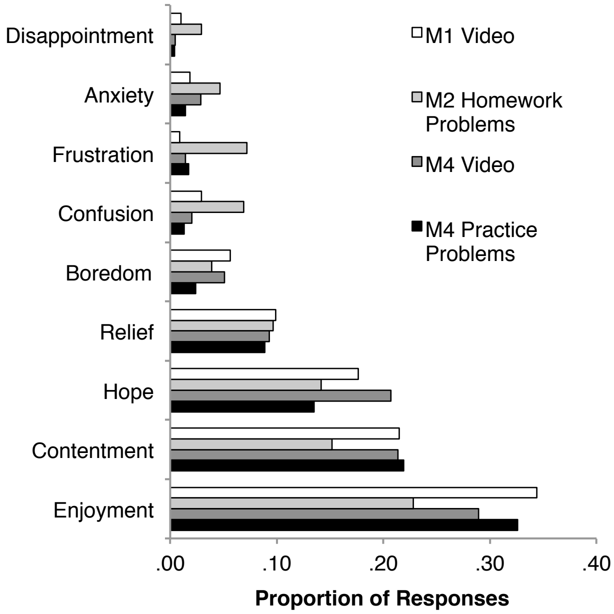

Figure 3. Proportion of emotion self-reports by activity type

We also note that the content-level emotions varied with regard to certain activities. For instance, *Pride* was reported nearly 10 times more frequently in response to Module 4 Practice Problems than in Module 1 Video. *Frustration, Confusion,* and *Anxiety* were quite prominent during Module 2 Homework Problem compared with Module 4 Video. *Relief*, on the other hand, did not fluctuate substantially among these four content-level reports. *Hope* was more frequently reported in both of the video activities, while *Pride* was more frequently reported in the problem sets. Further research is needed to determine if indeed students expressed *Pride* more frequently in contexts of achievement such as completing a problem set. We would also need to consider a larger set of activities to establish if certain emotions occur more frequently and significantly among certain genres of content.

These course-level affect surveys highlight that students experience different emotions during different types of content in a MOOC. If MOOCs are able identify the prominent emotions associated with various types of content such as videos and problem sets, then instructors and course designers can provide appropriate support to learners when needed.

Q2. Which emotion pairs co-occur more than chance?

Bosch and D'Mello [4] investigated co-occurrence of emotions in a computerized learning environment. In their study, they employed a retrospective judgment protocol without any interruptions during the learning session. They determined which co-occurring emotions occurred more than chance by computing Lift scores [24] for each emotion pair. Lift is a technique from association rule learning that can be used to compare the observed co-occurrence of emotions to the level expected by chance. Lift of a pair of emotions (X, Y) is defined as ratio of Pr(X and Y) to Pr(X)*Pr(Y).

We identified co-occurring course-level emotions as follows. First, we only considered responses with exactly two emotion reports. Second, we only considered affective states that occurred at least 1% of the time. This restricted our analysis to *Anxiety*, *Boredom*, *Confusion*, *Contentment*, *Enjoyment*, *Frustration*, *Hope*, and *Pride*. Lift scores were calculated for all pairwise combinations of the above emotions. We used random sampling without replacement (1,000 iterations) and a sample size of 3,000 to compute 95% bootstrapped confidence intervals for the Lift scores. Lift scores above 1.0 with confidence intervals that do not overlap with 1.0 are considered to occur more frequently than chance.

We computed Lift scores for all 5 course-level affect reports. There were 92 distinct co-occurring emotions and a total of 5,189 emotion pairs as reported by 3,591 learners. The results are shown in Table 1. We note that only 5 out of the possible 92 emotion combinations co-occurred at levels above chance and these mainly involved the learning-centered affective states of *Confusion*, *Frustration*, *Boredom*, and *Anxiety*. The *Confusion* + *Frustration* pair had the highest Lift score, which is consistent with [4] despite considerable differences in the temporal resolution of the analyses. Somewhat surprising is the fact that boredom co-occurred with both confusion and frustration, but this might be attributed to the coarse-grained nature of the emotion self-reports (e.g., boredom could occur for some activities and confusion for others within the same session).

Table 1. Lift of frequently co-occurring emotion combinations

Emotion Pair	Mean (SD)	Confidence Interval
Anxiety + Frustration	1.22 (0.17)	(1.21, 1.22)
Boredom + Confusion	1.06 (0.23)	(1.05, 1.06)
Boredom + Frustration	1.39 (0.43)	(1.39, 1.4)
Confusion + Frustration	3.22 (0.41)	(3.21, 3.23)

Q3. How do individual and co-occurring emotions relate to dropout?

We coded a student as having "dropped out" if he or she had no interaction events in the last module (Module 8). Table 2 presents partial Spearman's *rho* between dropout and course-level discrete emotions that comprised at least 1% of the data and corresponding exceeding chance. We partialled out the number of emotion reports per student in order to control for the steep rate of attrition and subsequent dropout bias in our data.

The results indicated that *Anxiety*, *Confusion*, and *Frustration* were significantly positively correlated with dropout, which is what we would expect. It was surprising, however, that *Hope* was also positively correlated with dropout, suggesting that these hopeful students might have become disillusioned by the MOOC. *Relief* was weakly negatively related to dropout, albeit non-significantly.

Table 2. Partial correlations between affect reports and dropout

Emotion/ Combination	*rho*	*p*
Anxiety	**.155**	**.000**
Boredom	.004	.954
Confusion	**.122**	**.019**
Contentment	-.035	.243
Enjoyment	-.028	.184
Frustration	**.251**	**.003**
Hope	**.046**	**.018**
Pride	.034	.476
Relief	-.081	.145
Anxiety + Frustration	.107	.458
Boredom + Confusion	-.088	.684
Boredom + Frustration	-.018	.956
Confusion + Frustration	.177	.263

The most valuable payoffs of this study for learning scientists and MOOC designers are the positive, though weak, correlations between *Frustration*, *Anxiety*, *Confusion* and dropout. The next step is to identify the causes or partial causes of those negative emotions. For example, students reported three times more *Frustration* in Module 2 Homework Problems than in other selected activities, suggesting that the homework problems in this module might need deeper consideration.

4. DISCUSSION

We recorded student affect in a MOOC setting and analyzed them with respect to both individual emotions and co-occurring pairs. This study marks the first large scale analysis of self-reported emotion in a MOOC context. We found that students experience a rather diverse set of emotions while completing a MOOC that previous work that has focused on lab- or in-class learning. Particularly interesting was the finding that *Hope*, *Enjoyment*, and *Contentment* were the most frequently reported emotions in the MOOC context, given that they are rare in shorter learning sessions studied in previous work [9].

We also found that some emotions fluctuate depending on MOOC content. This is an especially valuable finding for both instructional designers and researchers. From a learning design perspective, if we know how students are affectively reacting to different types of content, we can adjust the course materials accordingly.

Our findings also contribute to the dropout problem in MOOCs. Despite researchers capacity to predict dropout [25,26], we still lack a robust understanding of student dropout. We identified specific emotions and emotion combinations that correlate with student dropout, yielding an affective perspective to the dropout problem.

5. LIMITATIONS AND FUTURE WORK

There are several limitations with this exploratory study. First, the content was released to students all at once, so they could complete the course in any order they desired. This limits the feasibility of temporal analysis of the data. Second, since this study was based on a live course, we could not ask students to self-report their affective states as frequently as in a lab setting. This limits use of the data for more fine-grained sequential analyses.

Our analyses also point to several opportunities for future work. One promising avenue is sensor-free affect detection for MOOCs [2]. It would be valuable to model student emotion based entirely on clickstream data provided by edX and other online learning platforms. This would allow for far more frequent affect measurement and more timely affect intervention. If, for instance, we know, based on log data, that a student is *Frustrated*, and we know that *Frustration* correlated with dropout, we can launch pedagogical scaffolds to help the student manage his or her *Frustration*.

A second opportunity for future work is to analyze changes in emotions across the time. There are many questions that can be asked along this front. How do emotions change over the duration of an activity, a session, or the entire course? What is the affective trajectory of a successful MOOC student? Further research is needed to map emotion trajectories over the duration of the course so that we better understand the relationships between emotions, their temporal dynamics, and educational outcomes.

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