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Beyond positive and negative emotions: Looking into the role of achievement emotions in discussion forums of MOOCs

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ABSTRACT

Millions of students register for Massive Open Online Courses (MOOCs) to look for opportunities for learning and self-development. However, the learning process usually involves emotional experience, which may affect students' participation in the course, eventually resulting in dropping out along the way. In this study, we quantify this effect. Particularly, this research goes beyond focusing on only the single dimension of positive or negative emotions as many prior studies do. Instead, informed by the control-value theory, a more integrated framework of achievement emotions is applied in order to gain a comprehensive understanding of the role of emotions in MOOC students' learning experiences. Specifically, we first built and validated a machine learning model to automatically detect the achievement emotions in the forum posts. Then survival analysis was used to quantify the influence of achievement emotions on student dropout. The results show a different influencing mechanism for expressed and exposed achievement emotions on student survival in the MOOC course. Implications of the results are then discussed in terms of intervention design to improve student retention in MOOCs.

1. Introduction

With the recent development in open educational resources in both industry and academia, Massive Open Online Courses (MOOCs) have taken the center stage of discussion especially in the higher education sector (Reich, 2015; Wautelet et al., 2016). MOOCs can enable thousands of students to take courses at their convenience without cost or at low cost. It is largely because they provide a specific means for enabling more equitable access to learning that MOOCs have gained popularity in recent years (Tang and Carr-Chellman, 2016). In spite of all their potential, a significant concern about MOOCs is the extremely high attrition rate (approximately 90%) that has been reported (Hew & Cheung, 2014). Such a high dropout rate has often been cited as a scale-efficacy tradeoff (Onah, Sinclair, & Boyatt, 2014). While the reasons for dropping out are diverse in MOOCs, studies have shown that students' emotions evidenced in their learning process can significantly affect students' continued participation (Dillon et al., 2016; Dillon et al., 2016; Hillaire, Iniesto, & Rienties, 2017).

Understanding the role of emotion becomes more important especially if we consider the gradual nature of attrition in MOOCs. Much of the research on MOOC dropouts centers on the summative metric of attribution, e.g., through conducting correlational analysis between dropouts with click-stream evidence of engagement (Ramesh, Goldwasser, Huang, Daumé III, & Getoor, 2013) or building dropout prediction models (Halawa, Greene, & Mitchell, 2014). However, several seminal works have shown that attrition takes place over time (Whitehill, Mohan, Seaton, Rosen, & Tingley, 2017; Yang, Wen, Howley, Kraut, & Rose, 2015). That is, while many participants either never engage in the course at all or drop out after the first week, a significant portion of participants remains in the course for several weeks and then drops out along the way (Yang, Sinha, Adamson, & Rosé, 2013). This suggests that there are students struggling to stay involved. Understanding the participation of struggling students as they struggle and ultimately quit the course can help find potential ways to provide appropriate intervention and scaffolds to support them. Investigations on struggling students from an emotional perspective are essential to understand their participation and learning experience. Emotions have been constantly identified as one of the key factors in influencing online learning commitment (Lee & Choi, 2011; Pillay, Irving, & Tones, 2007). Supporting these struggling students from the emotional angle may be the first low hanging fruit to improve the retention rate of a MOOC.

Emotion has a complex influence on learning and commitment. Positive emotion experienced during the learning process is not necessarily related with longer commitment in MOOCs and negative emotion may lead to a beneficial effect on learning outcomes (Barak,

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Watted, & Haick, 2016; Lee & Choi, 2011). In fact, emotions are more than a simple dichotomy of positive and negative emotions. In learning and academic settings, the kind of emotions that really matters to the commitment and outcomes are achievement emotions (Pekrun, 2006). Achievement emotion can be further deconstructed as positive activating, positive deactivating, negative activating and negative deactivating emotions according to the control-value theory (Pekrun, 2006). As an integrative framework to approach students' learning experiences, the control-value theory of achievement emotions may serve as the basis for instructors to design interventions to improve learning engagement in MOOCs. By contrast, research previously investigated the influence of the single dimension of emotions (positive or negative emotions) on attrition overtime (Dillon, Ambrose, et al., 2016; Dillon, Bosch, et al., 2016), without revealing the mechanism for different achievement emotions on student attrition.

This work focused on exploring achievement emotions and their complex impact on student dropouts in MOOCs. It aimed to understand how achievement emotions influence learner survival as they struggle and ultimately withdraw from a MOOC forum. Relying on an actual MOOC dataset, we first depicted a classifier that automatically predicted the different achievement emotions of students' posts in the MOOC forum. Then with reasonable accuracy, the built classification model was applied to all the posts to identify the four achievement emotions. Finally, a survival modeling technique was used to quantify the effect of different achievement emotions on student attrition longitudinally. The rest of the paper is organized as follows: we begin by discussing the literature and theoretical framework underlying this study. Next, we describe the dataset and the methodology used. Then, our analysis and results are presented. Finally, we discuss the results and summarize this study by anchoring it to the prior work.

2. Literature review and background

2.1. Dropout analysis in MOOCs

The hallmark of MOOCs is that enrolled learners are involved in the social learning with virtual unlimited peers (Reich, 2015). Participation in the course is the prerequisite for learners to benefit from the large-scale social learning. Conversely, the large number of attritions becomes the tradeoff to extend educational resources to the masses (Onah et al., 2014). Therefore, improving the retention rate of MOOCs has become a major focus of recent research.

Many studies explored the relationship between students' behavioral patterns and MOOC dropouts using the summative measure (e.g. Alraimi, Zo, & Ciganek, 2015). However, there are many different reasons for student attrition. While a lot of students never participate in the MOOC course or stop participating after the first week, a great portion of students who might have intended to complete a MOOC gradually disengages from the course. So, providing support for these struggling learners becomes an attainable initiative to maintain learner retention in MOOCs. Focusing only on the summative measure of attritions cannot provide efficient strategies to support these students. Another major trend of research on dropouts is to build prediction models in MOOCs with the aim of providing early interventions (e.g. Halawa et al., 2014; Li et al., 2016). Nevertheless, these models are usually based on behavioral engagement patterns, and therefore, they have limitations in suggesting pedagogically sound intervention designs.

A few studies have begun to look at the experience of struggling students in MOOCs in support of the effort to improve students' retentions. For instance, Yang et al. (2015) observed that learners who convey more confusion in their forum posts are less likely to complete the course. Wang, Kraut, and Levine (2012) examined the influence of social positional factors on student survival in the MOOC courses. Wen, Yang, and Rose (2014) applied data mining models to gauge learner motivation through cognitive engagement in MOOC forums and studied its association with student completion rates. Ramesh et al. (2013) conducted content analysis to investigate the relationship between sentiment and subjectivity of student posts and their disengagement. In particular, an obvious influence of motivation and cognitive engagement on learner commitment in MOOCs was detected, but the effect of emotions was relatively inconsistent with simple measures (Yang et al., 2015; Tang, Xing &Pei, 2018). Indeed, emotion has a complex influence on learning and commitment (Dillon, Ambrose, et al., 2016). While prior work offers an enriched understanding of learner survival in MOOCs through examining discussion forum posts, little effort has been invested in trying to understand students' emotions and how they affect students' attrition using an integrative framework.

2.2. Achievement emotions and learning

The control-value theory of achievement emotions (Pekrun, 2006) provides an integrative framework to understand emotions in academic settings. Achievement emotions are "goal-directed and appraisal-driven multi-componential psychological processes" (Jarrell, Harley, & Lajoie, 2016, p.290) directly related to achievement activities and outcomes (Pekrun, 2006; Pekrun & Perry, 2014). The control-value theory posits that emotions are triggered by individual subjective appraisals of control (e.g., self-concepts, self-efficacy, and outcome expectation) and value (e.g., perceived value) towards achievement activities and achievement outcomes (Pekrun & Perry, 2014). Therefore, the control-value theory adopts two dimensions of human affections to differentiate achievement emotions, valence (intrinsically positive or negative) and arousal (psychologically activating or deactivating) (Pekrun, Lichtenfeld, Marsh, Murayama, & Goetz, 2017). In doing so, the theory categorizes achievement emotions into four groups, namely positive activating, positive deactivating, negative activating, and negative deactivating emotions.

Positive activating emotions include enjoyment, hope, and pride. Learners with positive activating emotions are dedicated to the learning activities with positive appraisal of the activities and outcomes (Pekrun, 2006). The opposite side of positive activating emotions are negative deactivating emotions, including boredom and hopelessness (Pekrun et al., 2017). Generally, learners with negative deactivating emotions hold negative opinions about the achievement activities and outcomes without any intention of making an effort. In addition, positive deactivating emotions contain relaxation and relief. These emotions describe the condition where learners have a positive attitude to the activities and outcomes, but investing effort and time in these activities is not their priority. Negative activating emotions consist of anger, anxiety, and shame. Learners with negative activating emotions commonly focus all their time and strength on the learning activities, but have negative appraisals of the activities and outcomes.

Achievement emotions hold the potential of reinforcing or undermining learning performance and commitment. Specifically, achievement emotions influence cognitive and metacognitive learning strategies and then impact learning performance (e.g., Artino & Jones, 2012; Pekrun, Goetz, Titz, & Perry, 2002). For example, Artino and Jones (2012) found that positive activating emotions are triggers for learners to efficiently apply cognitive and metacognitive strategies. To the contrary, learners with negative deactivating emotions (e.g., boredom) are less likely to apply these adaptive strategies. Given the impact on learning strategies, achievement emotions are also expected to influence learner attrition, as the efficient use of cognitive and metacognitive strategies is closely related to the success of completing courses. For example, Daniels et al. (2009) insisted positive activating emotions (e.g., hope, enjoyment) were indicators of positive valence and agency of the goals and are thus negatively related to dropout rates in face-to-face courses. In contrast, student dropout has been listed as a potential outcome of negative deactivating emotions (e.g., boredom, hopelessness) because these emotions reflected a negative appraisal of control and value over the activities (Pekrun, Goetz, Daniels, Stupnisky,

& Perry, 2010).

In addition, achievement emotions not only affect individual learning, but also impact others in a shared social learning process. In collective settings, emotions are contagious in support of the construction of "collective emotions" (Barsade & Gibson, 2007). According to Schoenewolf (1990), emotional contagion is "a process in which a person or group influences the emotions or behavior of another person or group through the conscious or unconscious induction of emotion states and behavioral attitudes" (p.50). For example, people might develop empathy and thus become angry after chatting with an angry teammate. The emotional contagion transfers the affective signals to peers in a shared social setting, and these transferred signals do not only influence the emotional states of peers, but also their cognition, attitudes, and behaviors, as well as the dynamics of the social setting (Barsade, 2002). In addition, Hancock, Gee, Ciaccio, and Lin (2008) reported that emotional contagion also takes place in text-based computer-mediated communication. That is, achievement emotions emerging from the texts in the forums are also contagious to peers. Furthermore, Barsade (2002) hypothesized that the mechanism for emotional contagion differs by the valence (i.e., positive or negative) of emotions. Although his experiments in physical settings failed to confirm this hypothesis, understanding the power of different types of emotions is still integral in revealing the mechanism of how emotional contagions function in both online and offline settings (Barsade, 2002).

As a result, to mitigate attrition in MOOCs, both individual expressed and exposed emotions have to be investigated as MOOCs foster a social learning environment for thousands of learners. MOOC instructors are unlikely to maintain personalized interaction with each learner due to the massiveness of the course (Wang et al., 2012). Lacking instant feedback, interactive communications, and in-time support enhance the likelihood of students leaving their social communities (Yang et al., 2015). It becomes worse when students' emotional experience is not well fostered in their learning process. Moving towards more successful MOOCs in the future requires new interventions and mechanisms to help students regulate and manage their emotions in their social learning environments. Such interventions and mechanism design will rely on the ability to monitor and track students' emotional experience and also the understanding of the role emotions play in the context.

2.3. Emotions detection and attrition in MOOCs

We have to identify different achievement emotions by monitoring and tracking students' learning experience in MOOCs before we can affect their emotions to enhance their commitment. Further, we must also quantify the influence of achievement emotions on students' attrition in MOOCs before accurately designing effective intervention strategies and mechanisms.

Given the large enrollment in a MOOC, detecting emotions by traditional manual coding techniques and qualitative methods are time-consuming and impractical. So, researchers have to initiate automatic emotion detection attempts. Emotion detection is an established field of research in various disciplines such as computer science, robotics, social media research, and psychological sciences (Yang et al., 2015). In the educational field, many studies have also explored automatic emotion techniques for learning purposes. They usually use machine learning models to automatically detect student emotion changes over extended periods of time (Tang, Xing & Pei, 2018). Some of the established emotion detectors are constructed using physiological sensors to examine vocal patterns (Calvo & D'Mello, 2010). Baker and his colleagues conducted a series of studies to automatically identify students' emotions from a combination of observation data and log files (Baker et al., 2012; Pardos, Baker, San Pedro, Gowda, & Gowda, 2014). Rose and her team designed automatic emotion detectors using emotion-related keywords in online forums (Wen et al., 2014). In our study, we used only the information readily available in MOOC forums for emotion identification for easy application in the future. At the same time, we also went beyond simply using emotion-related keywords. A more sophisticated feature set was used to achieve better performance in emotion detection.

To quantify the effect of achievement emotions on student attrition in MOOCs, survival analysis was used in this study. Survival analysis is defined as a set of methods to analyze data where the outcome variable is the duration until an event of interest occurs (Miller Jr, 2011). Compared with ordinary regression models, survival analysis has the advantage of modeling the duration and also the actual status of dropouts simultaneously and precisely. Survival analysis has also been widely used in social sciences research (Xing, Goggins & Introne. 2018). For instance, Wang et al. (2012) used it to examine how social support influences patients' commitment in online health support groups; Yang et al. (2015) applied survival modeling to investigate how confusion influenced the length of students' engagement in MOOCs. Building upon previous research, our study implemented survival analysis to explore the role of achievement emotions in influencing student attrition in MOOCs.

2.4. Summary

Compared with other attribution studies in MOOCs, this study will fill the gap to reveal the role of achievement emotions in MOOC forums and how it relates to students' engagement in the forum. From methodological perspective, this study will provide a more comprehensive way to detect the achievement emotions in contrast with existing studies for emotion detection. We will further model the temporal effect of achievement emotions on students' engagement in MOOC forums which shows advantage over other studies to analyze the accumulated influence of certain factors on students' engagement. The overall purpose of this study to understand the complex interaction between achievement emotions and students' dropout in MOOC forums. We intend to demonstrate how such emotions affect learners' survival as they struggle and ultimately drop out from a MOOC forum.

3. Methodology

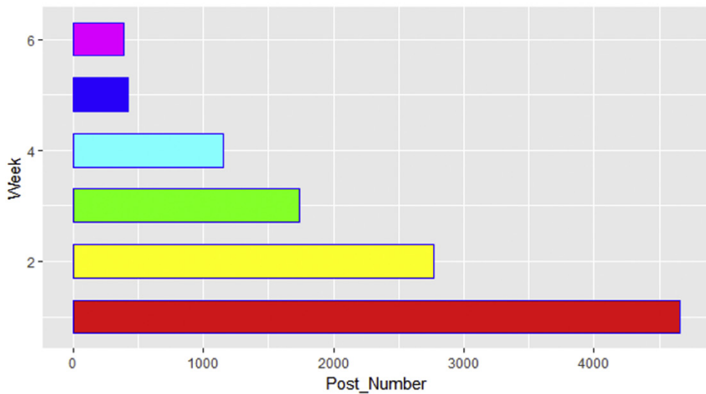
3.1. Research dataset and context

The dataset used in this research was derived from a Coursera MOOC offered by a large public research university in the United States. This course was selected because 1) this was a highly valued MOOC by many online portals and students; 2) its course design (e.g., course format, course length, discussion forum settings) and student population (e.g., number, profile) was exemplary (Bonafini, Chae, Park, & Jablokow, 2017). With that being said, empirical findings resulting from this dataset were more likely to be replicated with other MOOCs. The course lasted for six weeks in the summer of 2014. Each week focused on a specific topic aligning with the theme of the course. Each module came with an exclusive forum wherein students voluntarily participated and also revisited prior forums at will. In addition, the course also included two general discussion forums separately dedicated to sharing projects and reflections for instructors and students. Additional forums were created to provide logistical support for students, including self-organizing learning groups, resolving technical issues, and submitting suggestions/complaints about the course. In total, there are 2084 active forums users who posted at least once in the course forum and 13,513 posts.

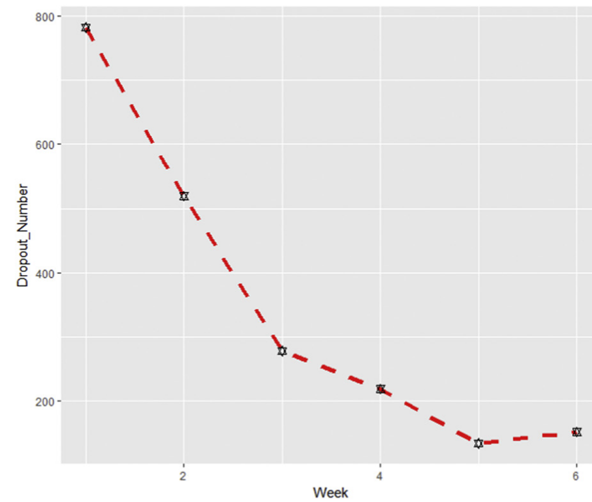
Fig. 1(a) gives an overview of the number of posts over the six weeks and Fig. 1 (b) provides information on the number of students who remained active in the discussion forum during the course.

3.2. Achievement emotion detection

Most previous research on communication in MOOC forums is based



(a). The number of posts over six weeks



(b). The number of dropout students over six weeks

Fig. 1. Descriptive statistics in the MOOC forum.
(a). The number of posts over six weeks (b). The number of dropout students over six weeks

on hand-coding relatively small samples of posts (Barak et al., 2016; Kop, 2011). These qualitative techniques are impractical or at least require tremendous effort in coding the 13,513 posts. To overcome this methodological challenge, machine learning models were built to automatically detect the achievement emotions of each post. Building and validating machine learning models involved three steps: first, human coders manually categorized a sample of posts into different achievement emotions. Their judgements of the posts served as the ground truth or training data. Second, all the coded posts were represented by a set of features as input into machine learning algorithms. Third, the machine learning model was built and validated using various algorithms on the features. After building the machine learning model, this model would be applied to the remaining posts so that every post could be automatically categorized into different achievement emotions.

To create the training dataset for the first step, 800 posts were randomly sampled from the entire dataset. Then two graduate researchers independently coded the posts to identify achievement emotional states. To assess the inter-rater reliability of the coding, Cohen's Kappa was calculated and reached 0.864, indicating high agreement between the coders. Samples of the post coding were illustrated in Table 1.

Students express their emotion explicitly or implicitly via different ways and can use different language strategies. To capture these different cues, three kinds of textual features were extracted for the second step as shown in Table 2, including language summary features, linguistic features, and Latent Dirichlet Allocation topic features. Language summary features were used to capture the generic diversity of languages in students' expression of their emotions. Linguistic features were used to calculates the degree to which students use different categories of linguistic dimensions (e.g. tense, grammar), and psychological constructs (e.g. positive or negative affect). The language summary features and linguistic features were extracted using the Linguistic Inquiry and Word Count (LIWC) library (Pennebaker, Boyd, Jordan, & Blackburn, 2015). Selection of the LIWC dictionaries relied on their relevance to the achievement emotions. For instance, *we* (*us*, and *ours)* often addressed the feeling of companionship and positive emotions. Punctuation (question mark, exclamation) was often associated with

Table 2
The feature set.

Language summary features (LSF)
word count, words > 6 letters, dictionary words, words per sentence, emotional tone, clout, authentic
Linguistic features (LF)
Grammar: verb, adj, numbers, quantifiers
Punctuations: period, comma, question mark, exclamation, quote
Function words: pronouns, articles, conjunctions, negations, prepositions
Affect and Social: anger, sad, social, family
LDA topic features (TF)
Relative, motion, space, time, personal concerns, work, leisure, home, informal, swear, assent

Table 1
Post coding example.

Post number	Post content	Emotional states
Post 1	*I stretched, I pulled, I crawled, I walked and I ran. I thoroughly enjoyed this course and for me the format was very applicable to the subject material. Defining, measuring and quantifying creativity, innovation and change is a difficult task. A sincere thank you to all the XX team and my fellow students and participants. I am still enjoying the growing pains; may it last a lifetime.*	Positive activating
Post 2	*I couldn't help agree with that more. Doodling is like walking a dog with no specific destination. You could just let your thoughts flow like ink from a fountain pen. Also, it is like day dreaming, we could relax without a constraint. I sometimes even 'see' myself flying over me and shoot up in the sky seeing the surroundings from an bird eye view. And I sometimes have weird dreams where I got inspired. Doodle, perhaps, is the most conscious act we could control.*	Positive deactivating
Post 3	*The class is over and still I haven't heard anything so I must assume that nothing will be done. I'm deeply disappointed. Not so much becasue I did the required assignments and for most of the assignments did extra peer evaluations. That was my choice and I enjoyed it but rather that no one cared enough to look into this technical problem or even had the courtesy to reply.*	Negative activating
Post 4	*Sorry to say that I wanna un-enroll this course because I found it unhelpful. Anyway, nice meeting all of you!: D*	Negative deactivating
Post 5	*Oh, my survey result is 54, i can't remember it very clearly, but i know i'm in the middle adaptive.*	N.A.

certain emotions. In addition, language summary features and linguistic features were very generic and not tailored to the content of this particular MOOC context. Studies have found that different topics can convey different types of emotion and information (Buis, 2008). Therefore, Latent Dirichlet Allocation (LDA) was used to derive latent topics and representative words from each topic, and these derived words were then collected to become a dictionary. Then each LDA topic feature computed the frequency of words in every post matching the corresponding dictionary.

To optimize the performance of the machine learning model, four kinds of classic supervised machine learning algorithms were employed in the third step: Naïve Bayes, Logistic Regression, Support Vector Machines (SVM), and Decision Tree. Details about these algorithms can be found in Kotsiantis (2007) and Xing and Du (2018). The performance of all the algorithms was evaluated based on 10-fold cross validation to demonstrate the robustness of the prediction performance. Classical metrics, area under curve (ROC_AUC) and Kappa values were used to show the actual performance.

3.3. Survival analysis

In this study, we examined how achievement emotions at a time point influenced the subsequent tendency of a student to drop out of the MOOC. Compared with standard regression models, survival analysis can estimate the truncated nature of time series data in a less biased manner (Yang et al., 2013). The Hazard Ratio, as a common measure (Klein & Moeschberger, 2005), was used to explain the influence of an independent variable on the probability of a student's dropping out. Parametric regression of survival analysis was used with the Weibull distribution of survival times. All the active students who contributed to the MOOC forum were included. The interval time was defined as the number of participation days. The start point of participation was the timestamp for the first post, and the end point was the timestamp of the last post within this course.

3.4. Dependent variable

Dropout: A student was considered a dropout from the MOOC forum if the student had no activities in the discussion forum. Therefore, student dropout was a binary variable, a true variable if a student has forum activity in the last week, and a false variable otherwise.

3.5. Control variables

Average Post: This variable was the average number of posts a student contributed to forums in a week. It could be considered as a baseline for measuring students' engagement.

Thread Starter: Students who started conversations might be different from those who participated in them. This variable was quantified as the average number of threads a student start in a week.

3.6. Independent variables

Expressed Emotion (four variables): These independent variables measured the average achievement emotions a student had expressed in a week. It was calculated by the total number of posts falling into certain achievement emotions divided by the number of weeks the student contributed to the MOOC forum. Since achievement emotions were deconstructed into four sub-emotions, four variables were built for expressed achievement emotions: expressed positive activating emotions (ExprPA), expressed positive deactivating emotions (ExprPD), expressed negative activating emotions (ExprNA), and expressed negative deactivating emotions (ExprND).

Exposed Emotion (four variables): These independent variables measured the average achievement emotions a student was socially exposed to per week. It was calculated by the total number of posts in the threads initiated by the student falling into certain achievement emotions divided by the number of weeks the student initiated a discussion. Similarly, four variables were created by exposed emotion: exposed positive activating emotions (ExpoPA), exposed positive deactivating emotions (ExpoPD), exposed negative activating emotions (ExpoNA), and exposed negative deactivating emotions (ExpoND).

Table 3
Machine learning model performance.

	Metric	LSF	LF	TF	LSF + LF	LSF + LF + TF
Naïve Bayes	ROC_AUC	0.72	0.71	0.54	0.73	0.73
	Kappa	0.22	0.24	0.03	0.21	0.18
Logistic Regression	ROC_AUC	0.77	0.82	0.71	0.81	0.83
	Kappa	0.12	0.45	0.01	0.36	0.45
SVM	ROC_AUC	0.90	0.90	0.79	0.86	0.91
	Kappa	0.57	0.55	0.41	0.46	0.61
Decision Tree	ROC_AUC	0.78	0.79	0.76	0.72	0.56
	Kappa	0.58	0.56	0.45	0.46	0.52

4. Results

4.1. Achievement emotion detection results

Using different features and various algorithms, machine learning models were built to automatically identify different kinds of achievement emotions in MOOC forum posts. Table 3 shows the results for the performance of the machine learning models. By comparing the ROC_AUC and Kappa values, SVM has the highest performance with ROC_AUC (0.91) and Kappa (0.61) when using all the language summary features, linguistic features, and the LDA topic features. The prediction performance of the machine learning model using the SVM algorithm was comparable to other machine learning models built in similar forum contexts (Dalal & Zaveri, 2011; Khan, Baharudin, Lee, & Khan, 2010).

This built Decision Tree model was further applied to the remaining posts in the MOOC forum. Table 4 reports the descriptive statistics of related variables for different achievement emotions in the MOOC forum and also the two control variables for the survival analysis in the next section.

4.2. Survival analysis results

To quantify the influence of expressed and exposed achievement emotions on student attrition, survival analysis was conducted while controlling the effects of the average number of posts and thread starters. Effects were quantified using hazard ratio to illustrate the influence of a predicated variable on the probability of students' dropout. Since all the variables were standardized in this study, the hazard rate predicted the change in the probability of a student's attrition from MOOC forums when the number of these eight independent variables increased a unit. Table 5 and Fig. 2 show the survival analysis results.

Table 4
Descriptive statistics for the survival analysis.

	Mean	Median	SD	Min	Max
AveragePost	2.25	1.00	2.82	1.00	54.17
ThreadStarter	0.41	0.00	0.63	0.00	6.00
ExprPA	0.73	0.5	1.12	0.00	18.00
ExprPD	0.56	0.33	0.82	0.00	12.33
ExprNA	0.36	0.00	0.62	0.00	10.33
ExprND	0.30	0.00	0.59	0.00	7.00
ExpoPA	45.15	26.00	52.94	0.00	331.00
ExpoPD	36.81	21.00	42.06	0.00	255.00
ExpoNA	14.74	9.00	16.32	0.00	119.00
ExpoND	14.20	8.25	15.89	0.00	118.00

Table 5
Survival analysis results.

	Model 1		Model 2		Model 3	
	Hazard Ratio	*p*	Hazard Ratio	*p*	Hazard Ratio	*p*
AveragePost	0.891*	0.040	0.418	0.062	0.381*	0.036
ThreadStarter	0.848*	0.044	0.761**	0.003	0.733**	0.001
ExprPA			1.183	0.517	1.081	0.760
ExprPD			1.508*	0.035	1.610*	0.022
ExprNA			1.759**	0.003	1.944***	0.000
ExprND			0.837	0.340	0.873	0.480
ExpoPA					10.267	0.059
ExpoPD					0.066*	0.019
ExpoNA					3.370*	0.036
ExpoND					0.240*	0.027

* : $p < .05$.
** : $p < .01$.
*** : $p < .001$.

Model 1 shows the influence of the control variables of the average number of weekly posts and started threads on students' survival duration in the MOOC. The hazard ratio for AveragePost was 0.891, representing that students who contributed a standard deviation more posts than the mean were 10.9% (100% * (1–0.891)) more likely to survive in comparison with students with a lower number of average posts. Similarly, the hazard ratio for thread starters was 0.848, indicating that students who started a standard deviation more threads than the average were 15.2% more like to stay engaged in the MOOC.

Model 2 demonstrates the impact of students' expressed emotions on their dropout when controlling for the average number of posts and thread starters. It showed that both expressed positive deactivating and expressed negative activating emotions significantly decreased the survival rate. Specifically, students expressed positive deactivating emotions one standard deviation more than the average were 50.8% (100% * (1.508–1)) more likely to quit the course. The dropout probability for students expressing negative activating emotions was even higher (75.9%) than those who expressed deactivating emotions. Students' expressed positive activating emotions and negative deactivating emotions had no influence on students' survival time in the course.

Model 3 indicates the effect of exposed emotion on student dropout while controlling for the average number of posts, thread starters, and the expressed emotion variables. As a whole, it showed that exposed emotions had stronger influence on the commitment of students to the MOOC course than students' expressed emotions. To illustrate the effect, students exposed to positive deactivating emotions one standard deviation more than the average were 93.4% likely to survive in the course. Students were 237% more likely to quit when exposed to one standard deviation more of negative activating emotions. Students exposed to one standard deviation more of negative deactivation were surprisingly 76% more likely to survive in the MOOC course. Students' exposed positive activation had no influence on students' commitment to the course.

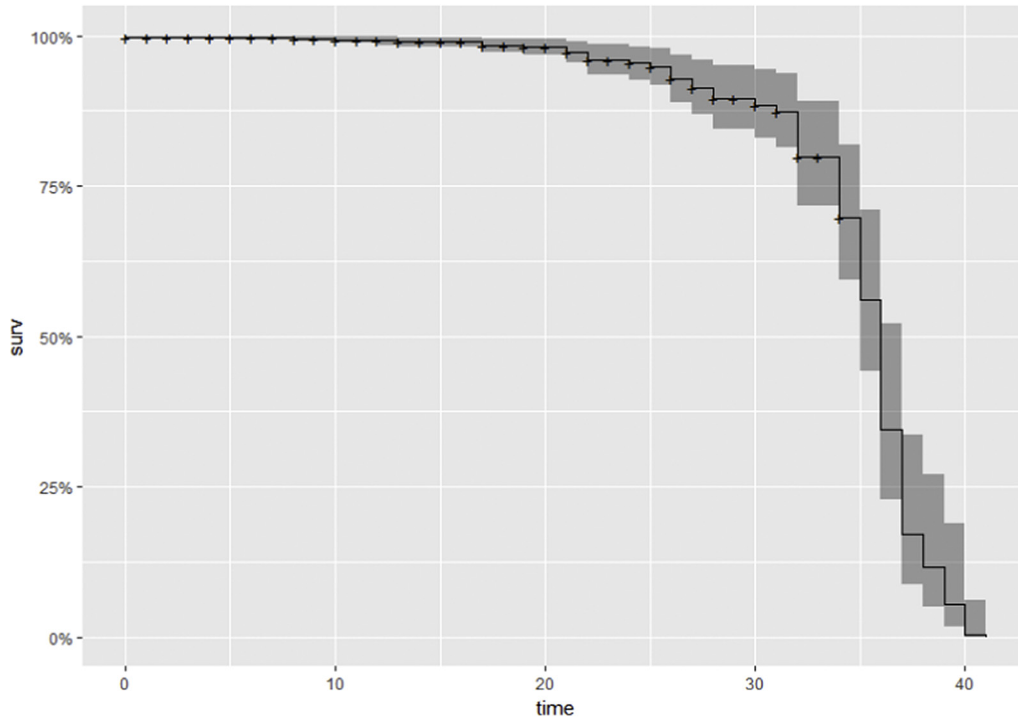
5. Discussion and conclusion

Increasing the retention rates of MOOCs is tremendously important for their future adoption. In this study, we looked beyond the dichotomy of only positive and negative emotions, using an integrative framework of achievement emotions to examine their influence on students' commitment in MOOCs. An accurate machine learning model was built to automatically detect the achievement emotions in the forum posts. Then survival analysis was applied to quantify the effect of achievement emotions on students' continued participation in MOOCs. The findings are as follows: first, students' exposed achievement emotions in the community have a stronger influence on student survival than their expressed achievement emotions; second, both expressed negative activating emotions and exposures to these emotions are significantly related to attritions, but students' exposures to negative activating emotions contribute more to the dropouts; third, only the exposure to deactivating emotions is positively related to learner survival; especially, the exposure to positive deactivating emotions is the largest positive contributor to learner survival; fourth, surprisingly, neither the students' expressed nor exposed positive activation has any effect on student survival in the course.

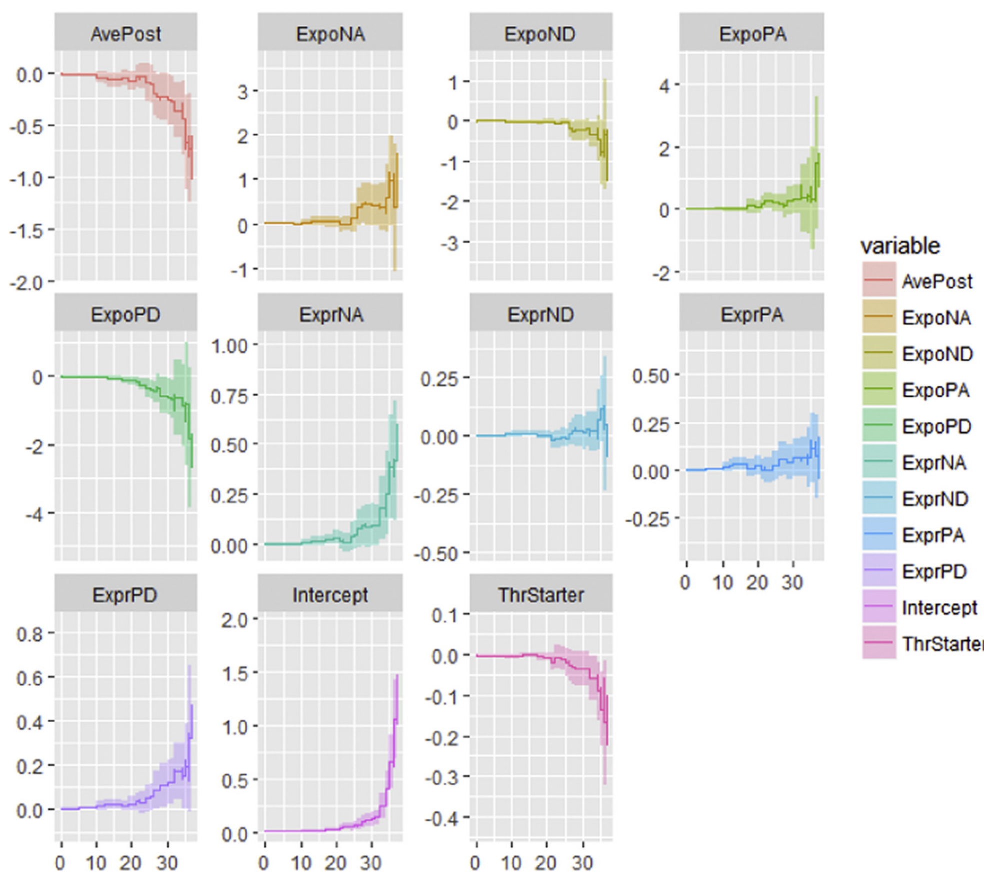
It is interesting to find that students' emotional exposures to their peers' posts have a stronger influence on their retentions than their own expressed emotions. This conclusion corroborates the relationship between confusion and dropouts in MOOCs (Yang et al., 2015). In that study, Yang et al. (2015) reported that students' exposure to their peers' confusing posts was more likely to result in dropout than the expressed confusion in their own posts. To explain this difference in the influence of emotional exposure and individual emotions on learner commitment in MOOCs, we refer to seminal works on emotional contagions (Barsade, 2002; Hancock et al., 2008; Kramer, Guillory, & Hancock, 2014). The results of this study confirm the existence of emotional contagions in the text-based forums in MOOCs (Chen, Gao, Yuan, & Tang, 2019; Hancock et al., 2008; Kramer et al., 2014). In particular, the massiveness of MOOCs leads to relative absent interactions between instructors and learners but highlights the importance of forum interactions. Our guess is the power of emotional contagions is reinforced in such a peer-based community as MOOCs. Once emotional contagions take place, receivers' individual emotions as well as behaviors might be transformed with a tendency to converge with the senders, potentially resulting in the improvement of the receivers' learning achievement (Barsade, 2002; Burić, 2019; Chen et al., 2019).

In addition, if students express negative activating emotions or if they are exposed to any of these emotions expressed by their peers, these students are less likely to maintain course retentions. In particular, the exposures to negative activating emotions have the larger influences on the dropout. This finding adds to the discussion about the power of different types of emotions during the course of emotional contagions. Barsade (2002) discusses the power of emotions with different valences in the process of contagions, but existing empirical evidence might not be able to determine whether positive or negative emotions have larger influences. This research following the control-value theory of achievement emotions investigates an additional dimension of emotions, activation/arousal, beyond the dichotomy of positive and negative emotions (Pekrun et al., 2017; Poitras, Harley, & Liu, 2019). The influence of exposures to negative activating emotions on learner retention is larger than any exposures to deactivating emotions (e.g., positive deactivating and negative deactivating emotions). Our guess is that activation/arousal might be an alternative sector determines which types of emotions dominate the process of contagions.

Furthermore, only exposures to deactivating emotions, especially the exposure to positive deactivating emotions, contribute to learner survivals. We suppose this phenomenon results from the features of MOOCs, an informal and self-directed learning community (Xing, Chen, Stein, & Marcinkowski, 2016). For most learners, external obligations significantly occupy potential time and effort dedicated to the course. Given the influence of emotional contagions, they might expect a less pressured emotional climate (Burić, 2019). Thus, being largely exposed to the deactivating climate in this course, students might improve self-efficacy or increase motivation to complete the course. This conclusion provides insights for the facilitation of discussion forums in MOOCs. A deactivating emotional climate might benefit the effort to improve the course retention rates. In addition, this finding further supports the argument that emotion has a complex influence on learning as negative emotions are not always detrimental to students learning achievement (Barak et al., 2016; Yang et al., 2015). Besides the valence, activation also influences how learning is accomplished (Pekrun et al., 2017;



(a) Overall survival curve



(a) Predicting variable effect on survival

Fig. 2. Survival analysis visualization for the variables.
(a) Overall survival curve. (b) Predicting variable effect on survival

Poitras et al., 2019).

Moreover, positive activating emotions (e.g., enjoyment, joy, pride) in both personal posts or others' posts have no influence on learner survivals. This is different from the findings of Pekrun et al. (2017) and Artino and Jones (2012). The decreased influence of positive activating emotions might result from the relatively loose structure of MOOCs or learners' different goals of enrolling in a MOOC (Xing et al., 2016). Learners without an intention of completing the course before enrolling are still very likely to drop out although they might enjoy or take pride in learning in the course. However, this does not imply positive activating emotions are not important in MOOCs. It is still vital to provide learners with the sense of enjoyment, happiness, and pride in MOOCs. Another surprising finding on expressed emotions is that negative deactivating emotions are also not related to dropouts in MOOCs, which refutes Pekrun et al. (2010). One guess is that learner dropout in MOOCs is not influenced by his/her achievement in such a flexible environment wherein learners can terminate the engagement at any moment.

This study has significant implications for MOOC adoption. Compared with traditional classrooms and online learning, students in MOOCs are often left unattended due to the class size (Dillon, Ambrose, et al., 2016; Dillon, Bosch, et al., 2016; Hew & Cheung, 2014). This study provides a way to detect students' expressed and exposed emotions during the learning process. Tracking and monitoring the emotional status in MOOCs can provide guidance for instructors to provide appropriate feedback for students. For example, when the overall climate in a MOOC forum is oriented to negative activating emotions, then the instructor should be especially careful and provide help to the students since such emotions have the strongest negative influence on student survival in the course. However, it is better if the overall emotion is positive deactivating since it has the largest positive influence on student engagement in MOOCs. The discovered emotional mechanism in MOOCs can also serve as the basis to design and develop automatic feedback and facilitation in MOOCs. The performance of built machine learning models for automatically detecting emotional states suggests that it is feasible to employ computer programs to analyze the conversations in MOOC forums. Specifically, the extracted features can be easily used to construct prediction models for other online learning groups (Xing, 2019). While the language summary features and linguistic features can be directly used in other contexts, the LDA topic features may need adaptations to the specific context used. This step for LDA topic feature extraction requires little effort.

This study has yielded practical implications for educators and practitioners in efficiently facilitating forum activities in online courses. First, educators and practitioners are supposed to increase their awareness of achievement emotions (Pekrun, 2006; Pekrun et al., 2010). Emotions influence students' commitment and achievement in an online setting (Barak et al., 2016; Yang et al., 2015). To support learner access, educators and practitioners need to not only focus on the valence of emotions (e.g., positive and negative) but also to take the activation dimension of emotions into consideration. Second, monitoring the overall emotional climate in the online forum is necessary for educators and practitioners to provide students with effective scaffolds (Pekrun et al., 2017; Poitras et al., 2019). This study further provides supplementary insights into facilitating the emotional climate by coordinating students expressed and exposed achievement emotions. Specifically, when the overall climate in a MOOC forum is oriented to negative activating emotions, then the instructor should be especially careful and provide help to the students since such emotions have the strongest negative influence on student survival in the course. However, it is better if the overall emotion is positive deactivating since it has the largest positive influence on student engagement in MOOCs. Third, educators need to figure out an appropriate way to exhibit their enthusiasm in an online forum and also efficiently transmit the positive power to their students (Burić, 2019). Emotions are contagious in various learning settings, disregarding with direct in-person context or not (Chen et al., 2019; Kramer et al., 2014). This study confirms students' expressed emotions are less vulnerable to the overall emotional climate. In other words, teaching in an online setting brings in additional challenges for educators to track the emotional climate, but it might also present an opportunity of amplifying the positive effect of their emotions. Fourth, the discovered emotional mechanism in this study can also serve as the basis for practitioners to develop automatic emotion intelligent scaffolds for online learners. The performance of built machine learning models for automatically detecting emotional states suggests that it is feasible to employ computer programs to analyze the conversations in MOOC forums. Specifically, the extracted features can be easily used to construct prediction models for other online learning groups. While the language summary features and linguistic features can be directly used in other contexts, the LDA topic features may need adaptations to the specific context used. This step for LDA topic feature extraction requires little effort.

An important limitation for this study is that our findings are correlational even though we address the longitudinal effects. We examined how different achievement emotions were associated with student survival in MOOCs and significant relationships were identified. While the results were consistent with previous findings that emotions influenced student survival, they could also be interpreted by individual student differences before enrolling in MOOCs. Additional control experiments might determine how emotions can influence student survival in MOOCs. Another limitation is that this study just focuses on students who have posted on the forum. Therefore, it might overlook the students who are lurkers, just reading and continuously participating in the MOOC forums. To study these lurkers, we may need specific measures and instruments to estimate or detect students' reading behavior. Similarly, the current measurement of the exposed emotions is also an indirect estimation of the students' reading of the posts. A more way of measuring posts reading can improve the reliability of the current study for estimating the exposed emotions.

There are a few directions for future research. First, even though our findings indicate the impact of achievement emotions on student survival varies by different expressed and exposed emotional states, the reasons behind them are unclear. Future studies can conduct interviews and surveys with students to examine why they stay or leave the course. Second, this study looked at only one MOOC course in a specific subject. A potential next step is to investigate emotions in multiple MOOCs with diverse subjects and instructional designs to determine the generalizability of the findings. For instance, how the achievement emotions interact with students who complete the course earlier. It might be interesting to further differentiate the expressed emotions in the initial posting and replying messages and their influence on students' engagement in MOOC courses. Third, maintaining continued participation and preventing dropout are only the first steps to improve the success of MOOCs. The overarching goal of offering MOOCs is to help learners achieve learning gains. It would thus be useful to study the extent to which different expressed and exposed achievement emotions affect students' learning performance.

Declaration of Competing Interest

The authors declare that they have no conflict of interests.

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