Understanding Engagement in MOOCs

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ABSTRACT
Previous studies about engagement in MOOCs has focused primarily on behavioral engagement and less attention has been paid to cognitive engagement. This may lead to incomplete or even incorrect understandings about students experience and learning in MOOCs. In this study, we use number of lectures watched as a proxy for behavioral engagement and number of pauses in lectures watched as a proxy for cognitive engagement. Results show that a large proportion of students who were behaviorally engaged (watching lectures) were not cognitively engaged—they almost never paused the lectures or they paused fewer and fewer times as the course went on. This may indicate that being behaviorally engaged does not necessarily mean being cognitively engaged. In addition, we also found that students' number of pauses in lectures is positively associated with achievement and improves the prediction of achievement.

Keywords
Cognitive engagement, behavioral engagement, MOOCs

1. INTRODUCTION
Engagement in MOOCs is usually measured by whether students complete learning activities or not (e.g. watching lectures and submitting assessments) and low engagement is used as an indicator of "at-risk" students [4]. However, studies of school engagement have proposed that engagement has three components: behavioral engagement, cognitive engagement, and emotional engagement, and that measuring engagement solely as task completion may focus only on behavioral engagement and overlook the multifaceted nature of engagement [1]. To explore the importance of cognitive engagement in MOOCs, this study measured both behavioral engagement and cognitive engagement in MOOC lecture watching to see: 1) whether individuals who were behaviorally engaged were also cognitively engaged, and 2) whether cognitive engagement adds information that is helpful in predicting academic achievement.

1.1 Behavioral engagement
Most of previous studies about engagement in MOOCs have focused on behavioral engagement: participation in academic activities [1]. One of the most commonly used engagement indicators in MOOC studies is participation in lecture watching. For instance, in the most frequently cited paper about engagement patterns in MOOCs, Kizilcec et al (2013) measured student weekly engagement as a function of whether they watched any lecture and submitted any assessment. By using these metrics of task completion, this study inherently conceptualized engagement as behavioral engagement. Similarly, measurements centered around behavioral engagement, such as time spent on lecture resources, have also been used in studies about the relationship between engagement and dropout [4].

1.2 Cognitive engagement
Cognitive engagement refers to the psychological investment in learning and ranges from memorizing to using self-regulated strategies to promote one's understanding [1]. In this study, we measure student's weekly cognitive engagement by how often they paused the lectures they watched (i.e., students stop the lecture while watching it). Some studies about MOOCs have explored the possibility of using video lecture clickstream data, the record of student click events, to measure cognitive engagement [3]. Among all the click events, the pausing event may indicate a higher level of cognitive engagement [3].

2. METHODS

2.1 Sample
This study uses data from one Coursera MOOC, Pre-calculus, offered by University of California, Irvine. It began on October 7th, 2013 and lasted for ten weeks. 50,676 students registered the course and data on 19,548 students who watched at leased one lecture after registration was used in this study.

2.2 Measurement
In this study, weekly behavioral engagement was measured by the number of lectures student watched each week while weekly cognitive engagement was measured by the number of pauses in lectures watched in a given week. In addition, we measured weekly academic achievement in two ways: students' total quiz score (the sum of scores a student got on each quiz he/she attempted each week) and students' average quiz score (the average score on quizzes attempted each week).

2.3 Analysis
We applied a standard clustering technique, K-means, to discover student engagement patterns based on the two measurements to see whether individuals who were behaviorally engaged were also cognitively engaged. We first standardized the engagement score within each week to take into account the difference in participation across weeks and thus to cluster students based on their relative similarity in engagement within each week. Then, we performed the clustering analysis separately for behavioral engagement and cognitive engagement. To get an optimal "goodness of fit" for the data, cluster silhouette, a measure of how similar an individual is to his/her own cluster compared to other clusters, was used to determine the number of clusters. For behavioral engagement, 4 to 9 clusters produced similar cluster

silhouette (above 0.7) and for cognitive engagement, 4 to 8 clusters produced similar cluster silhouette (above 0.6). Accordingly, we performed cluster analysis with all the possible choices. Finally, we chose 4 clusters for both of the two measurements because it gave us enough individuals in each cluster and all the clusters made sense from an educational perspective. In addition, to answer the second research question, we used regression with individual fixed effect to test whether cognitive engagement could predict academic achievement after controlling for behavioral engagement.

3. RESULTS

3.1 Clusters based on different engagement

The four types of behavioral engagement trajectories are: *1) "Strong enders"* (n=157; 0.8%) who watched more lectures than other groups and their average number of lectures watched decreased in the first six weeks but then increased to 50 at the end of the course; *2) "Slow decreasers"* (n=1367; 7.0%) who had a very similar pattern as "stronger enders" except that they kept watching fewer and fewer lectures till the end of the course; *3) "Quick decreasers"*(n=1598; 8.2%) who started at the same place as both "strong enders" and "slow decreasers", but the number decreased at a much faster rate; and *4) "Disengagers"*(n=16426; 84.0%) who watched around 2 lectures in week 1 on average and the number was kept under 1 for the following 9 weeks.

The four types of cognitive engagement trajectories are:*1) "Active stoppers"*(n=41; 0.21%) who, on average, paused each of the lecture they watched more than 10 times in most of the weeks; *2) "Constant stoppers"*(n=367; 1.9%) who, on average, paused each lecture they watched around 5 times in most of the weeks; *3) "Switchers"*(n=1719; 8.8%) who started at the same place as "constant stoppers", but their average number of pauses in lectures watched decreased quickly in the following weeks; and *4) "Continuers"*(n=17421; 89.1%) who almost never paused the lectures they watched or they didn't watch any lectures at all in some of the weeks.

Combining the two types of engagement (see Figure 1), we found that students in clusters with higher levels of behavioral engagement had a larger proportion of individuals who were cognitively engaged. For example, compared with "disengagers" and "quick decreasers", "strong enders" and "slow decreasers" have a smaller percent of "continuers" and larger percent of both "active stoppers" and "constant stoppers". However, being behaviorally engaged does not necessarily mean being cognitively engaged. For example, even though "strong enders" and "slow decreasers" watched the most lectures every week, around 45% them conducted fewer and fewer pauses as the course went on (defined as "switchers") and more than 20% of them almost never paused the lectures (defined as "continuers").

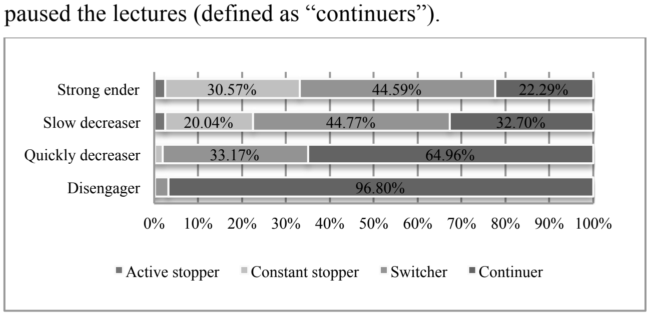

Figure 1. Distribution of cognitive engagement trajectories

3.2 Cognitive engagement and achievement

Using individual fixed effect model (see Table 1), we found that the number of pauses in lectures watched is predictive of both total and average quiz score after controlling for the number of lectures watched. For total quiz score, one more pause is associated with 0.33 points increase in total quiz score and 0.23 points increase in average quiz score. In addition, for both total and average quiz score, the models with the number of pauses in lectures watched fit significantly better than the models that only have number of lectures watched as the predictor. Overall, the results show that our measurement of cognitive engagement is positively associated with achievement and it can make a unique contribution in predicting achievement.

Table 1. Regression of engagement on academic achievement with individual fixed effect

	Total score		Average score	
Number of lectures	0.71^{***}	0.69^{***}	0.04^{***}	0.02^{***}
	(0.004)	(0.005)	(0.001)	(0.001)
Number of pauses per lecture		0.33^{***}		0.23^{***}
		(0.019)		(0.005)
N	79174	79174	79174	79174
R^2	0.281	0.284	0.017	0.054

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4. DISCUSSION

Our preliminary results indicate that it is important to take into account cognitive engagement. First of all, using only behavioral engagement may lead to an incomplete or even incorrect understanding about the activeness of students. As we found in this study, some students had relatively high behavioral engagement while decreasing or low cognitive engagement. We may fail to identity some "at-risk" students who visited most of materials but didn't truly engage with the content if we only measure behavioral engagement. In addition, cognitive engagement is found to have its unique contribution in predicting academic achievement and thus can give instructors extra information about student performance in a given course.

5. REFERENCES

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