Examining the Relations among Student Motivation, Engagement, and Retention in a MOOC: A Structural Equation Modeling Approach

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Abstract

Students who are enrolled in MOOCs tend to have different motivational patterns than fee-paying college students. A majority of MOOC students demonstrate characteristics akin more to "tourists" than formal learners. As a consequence, MOOC students' completion rate is usually very low. The current study examines the relations among student motivation, engagement, and retention using structural equation modeling and data from a Penn State University MOOC. Three distinct types of motivation are examined: intrinsic motivation, extrinsic motivation, and social motivation. Two main hypotheses are tested: (a) motivation predicts student course engagement; and (b) student engagement predicts their retention in the course. The results show that motivation is significantly predictive of student course engagement. Furthermore, engagement is a strong predictor of retention. The findings suggest that promoting student motivation and monitoring individual students' online activities might improve course retention.

Keywords

MOOC, retention, motivation, engagement

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Introduction

The large enrollment characteristic of massive open online courses (MOOCs) has generated excitement and attention (Pappano, 2012). A typical MOOC attracts around 20,000 students (Jordan, 2014b). However, a MOOC can potentially accommodate an unlimited number of students because, unlike a traditional classroom, a MOOC usually entails minimal student-instructor interaction. Also, unfortunately, unlike a traditional class, the student completion rates for MOOCs are low. The median of MOOC completion rates is about 6.5% with most completion rates below 10% (Jordan, 2014a).

Researchers have started to investigate possible reasons for attrition in MOOCs, most notably by examining student-level variables, such as motivation and social engagement (Khalil & Ebner, 2014; Rosé et al., 2014; Yang & Rosé, 2013; Yuan & Powell, 2013). However, studies thus far have rarely gone beyond observational and data-driven research. In contrast, our paper offers a theory-driven, structural model of MOOC student motivation, engagement, and retention.

Specifically, we posit that (a) motivation predicts MOOC students' course engagement; and (b) students' engagement predicts their retention in the course. We present this study as a means of providing a theoretically and empirically sound model for understanding MOOC students' motivation and how it is related to student behaviors in MOOCs. The ultimate goal is to provide practical guidelines to online educators for improving MOOC retention.

Literature Review

What influences MOOC retention?

Jordan (2014a) has gathered the available data from different online sources to explore factors that may affect MOOC completion. She mainly studied macro-level factors, especially course-level variables such as course launching time, total enrollment, and university rank. These were found to be unrelated to the completion rate. Course length was the only variable to have a negative correlation with the completion rate. As might be predicted, a lack of time is an obstacle, given that MOOCs serve as a supplemental, rather than principal, educational experience for most enrollees. As MOOC-based credit and degree programs develop, an increasing number of "full-time" MOOC students is foreseeable. Notwithstanding, "part-time" MOOC learners are still the biggest population.

More attention has been paid to student-level factors in order to understand the reasons for MOOC attrition (e.g., Khalil & Ebner, 2014; Rosé et al., 2014; Yang & Rosé, 2013). Most notably, internal and external factors related to student motivation were found to contribute to student dropout rates (Khalil & Ebner, 2014; Yuan & Powell, 2013). The internal factors include curiosity and enjoyment, while the external factors entail job-related development and future economic benefit (Yuan & Powell, 2013).

Rosé (2014) and Yang (2013) have conducted survival analysis on a MOOC dataset in order to understand the social behaviors that might be related to student dropouts on a week-by-week basis. They found some aspects of peer interaction were closely related to student retention. Generally, students who engaged other students in the discussion and stayed in the discussion for a long period tended not to drop out. In addition, students who participated during the very first week of the course tended to

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remain. Socio-cultural theorists hold that learning is a social process in which learners construct their own understanding through interaction with others (e.g., Lave & Wenger, 1991; Vygotsky, 1978). Social interactions essential for learning and community building are primarily peer interactions in MOOCs. "Lurkers" or others who do not participate in such MOOC interactions are more likely to quit.

Student Motivation, Engagement and Retention in MOOCs

Several researchers are beginning to examine various activity patterns of MOOC students, with the goal of creating broad student categories. Kizilcec, Piech, and Schneider (2013) leveraged k-means clustering to examine students in three MOOCs from Stanford University. Based on activity data, they found students broadly fit into four categories: completers (students who completed most assignments), auditing (students who did few-to-no assignments but engaged in watching videos), disengaging (students who did assignments early in the course, then later stopped participating), and sampling (students who watched videos only in the beginning of the course). Other researchers (Wilkowski, Deutsch, & Russell, 2014) defined four other categories of students: no-shows (students who register, but never participate), observers (students who want to see what an online course looks like or how it is taught), casual learners (students who are interested in a subset of the overall course), and completers (students who do all necessary work to finish the course). Another study (Hill, 2013) identified five categories of MOOC students: no-shows, observers, drop-ins, passive participants and active participants. While categorizing students based on student activity patterns is helpful for descriptive purposes, it provides little basis for understanding how a student's motivation might influence different interactions with the course.

There has been a great deal of research on student motivation in traditional schools and higher education settings, but the study of student motivation in MOOCs remains thin, despite the broadly-understood acknowledgement that student motivation is necessary to initiate learning and to sustain or adapt behaviors needed to achieve learning goals. The diminished social interaction within an online environment (i.e., a lack of face-to-face interaction between instructors and students) raises questions about students' engagement and motivation in MOOC classes, and how sustaining these may differ from face-to-face learning environments (Stewart, 2013).

Previous studies about online education emphasize the importance of social interaction within a community of learners engaged in course activities and with each other (Young & Bruce, 2011). As students engage with each other and with course activities, student motivation generally increases (Richards, 2011). Miltiadou and Savenye (2003) stated that interaction may increase students' persistence in an online course. Motivation is particularly important for retention in MOOCs because participants generally are not required to complete the course, and lack of motivation is a primary reason for students dropping out of a MOOC (Khalil & Ebner, 2014). Yuan and Powell (2013) argued that there might be different factors that influence MOOC students' motivation level, including "future economic benefits, development of personal or professional identify, challenge and achievement, enjoyment and fun" (p. 9). These factors largely are in accord with the findings of a survey conducted by Belanger and Thornton (2013), who found that students have different motivation to enroll in a MOOC; these researchers identified four relevant aspects: a) to support lifelong learning or gain the subject matter understanding; b) for fun; c) for the convenience of online learning; and d) to experience online education.

The different aspects of MOOC student motivation accord broadly with research on motivation outside the MOOC setting. For example, motivation theories commonly acknowledge two broad categories of motivation, intrinsic and extrinsic (Amabile, 1993; Ryan & Deci, 2000). Intrinsic motivation entails pursuing a task for the satisfaction, engagement or interest the task itself might provide. Extrinsic motivation entails pursuing a task for purposes beyond the task—for example, for pay or to earn a credential. Some earlier motivation theories saw these as wholly separate and even at odds with each other (Amabile, 1993; Deci, 1971), such that extrinsic motivation might undermine intrinsic desire to pursue an activity. However, more recent theories allow for complementarities between the two. For example, Ryan and Deci (2000) hold that extrinsic motivation spans a range from externally compelled to motivations that become integrated into the self in the presence of social ties and supports for developing competence. Amabile (1993) stated that human activity often entails both types of motivation. As an example, she might be both intrinsically motivated by the substance of the article she's working on and yet simultaneously extrinsically motivated to work on it right away to meet an editor's deadline.

In MOOC settings, students may bring intrinsic motivation, including curiosity and a desire for new experiences, alongside extrinsic motivation, including the need to obtain new skills or credentials that might be beneficial for their future study or work. Alongside intrinsic and extrinsic motivation is social motivation. For this paper, social motivation refers to social contexts and social interactions that may impel students to engage in the course. Ryan and Deci (2000) reported that social supports and social contexts can play an important positive or negative influences on motivation. Wentzel (1999) argued that social-motivational processes play an important role in driving individuals to achieve certain social goals. Social motivation in parallel with academic motivation may also influence students' academic outcomes (Wentzel, 1999). In the context of MOOC research, Yuan and Powell (2013) found that one of the elements of a MOOC that motivated learners to participate was an enjoyable social experience along with gaining subject matter knowledge and skills. Therefore, the social elements of a MOOC learning experience, which are afforded by discussion forums and participants' use of social networking, may play an important role in students' motivation.

In the MOOC environment, social motivation includes students' feeling of relatedness with peers. This coincides with the notion of "social presence," which has been studied in the online collaborative learning situations (e.g., Gunawardena & Zittle, 1997; So & Brush, 2008). Relative to face-to-face settings, learners in an online environment tend to have a reduced sense of connectedness and belonging, and this potentially impedes online peer interaction and engagement. Using survival models, Wen, Yang, and Rosé (2014) found that student motivation, measured by percentage of posts per week, and cognitive engagement, measured by level of language abstraction in forum posts, were significant predictors of dropouts. The results suggest that social interactions, which typically take place in discussion forums and posts in MOOCs, influence students' motivation to continue in the course or drop out.

Drawing on previous literature, we propose that MOOC learners' motivation is comprised of three dimensions: intrinsic, extrinsic and social aspects. This three-dimensional motivation model might not be exhaustive; however, we believe it captures the components that most deserve further investigation. Furthermore, in accord with existing literature that finds motivation impacts student engagement and outcomes (Lau & Roeser, 2002; Martin & Dowson, 2009), we propose that (a) motivation predicts student course engagement; and (b) student engagement predicts their retention in the course. In addition, the three dimensions of motivation correlate with each other. The conceptual model is shown in Figure 1.

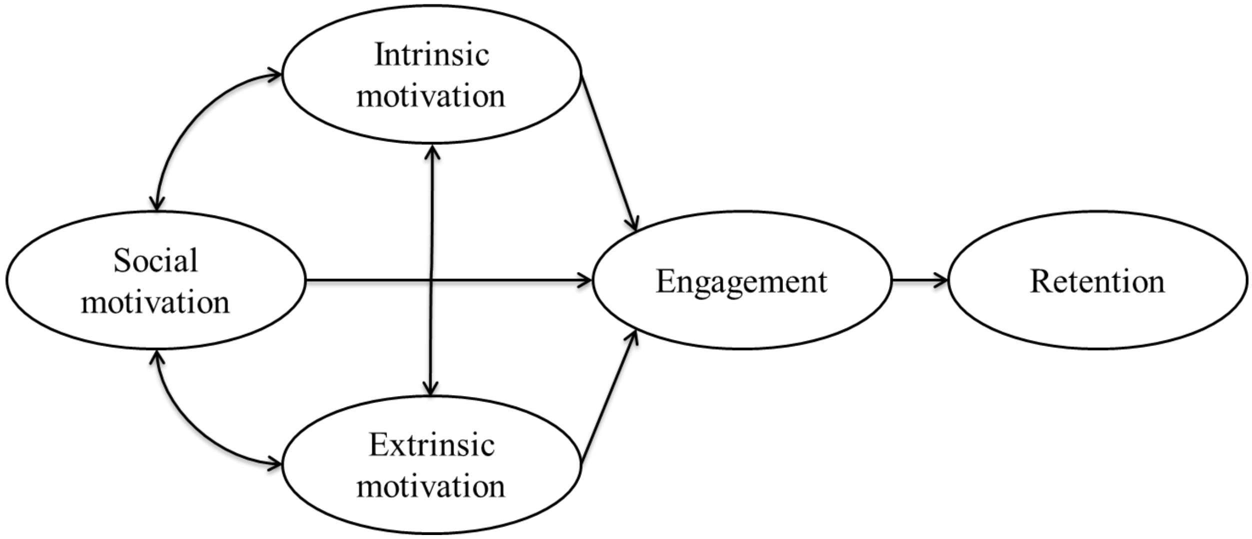

Figure 1. Conceptual Model

Method

Data Sources

Data in the current study were collected from a Pennsylvania State University MOOC titled Introduction to Art: Concepts and Techniques, an eight-week course offered by Coursera in 2013. A total number of 37,244 students had participated in this MOOC by the time of completion. After deleting those who did not complete the pre-course survey and those who did not participate in any course activities other than registering for the course, we retained a sample with 17,359 participants. The retained sample includes those who have completed the pre-course survey and have participated in at least one activity in the course (e.g., watched a lecture video, completed a quiz, or submitted an assignment).

Measures and Variables

The variables are operationally defined as follows in this study:

- *Intrinsic motivation*: general interest in taking the course.
- *Extrinsic motivation*: taking the course for external rewards, such as earning the course verification.
- *Social motivation*: taking the course for connecting with others.
- *Engagement*: participation in the course activities.
- *Retention*: the length of the period in staying in the course.

The model we have devised posits that MOOC participants may hold intrinsic, extrinsic, and social motivations. Participants' motivation was measured by five-point Likert items in a pre-course survey questionnaire, with 1 indicating that the statement is "not at all important" in the decision to enroll in the course and 5 indicating "very critical." Based on the available information from the pre-course survey, we identified one item measuring intrinsic motivation, four measuring extrinsic motivation, and two measuring social motivation. Information regarding student online activities, such as lecture video watching, quiz taking, etc., was extracted from the course data to measure student engagement in the MOOC. Retention is measured by the number of days between the start of the MOOC and the last day of activity by the student.

All the items are shown in Table 1. In summary, items measuring the three types of motivations are from the MOOC pre-course survey, and items measuring engagement and retention are from the course data.

Table 1. Measured Variables and Items

Variables	Item
Intrinsic motivation	*Interest:* I am taking the course out of general interest, curiosity, or enjoyment.
Extrinsic motivation	*Certificate:* I intend to earn a Statement of Accomplishment (or Verified Certificate) for this course.
	Credential: I am interested in earning a credential.
	Academic: The course relates to my current academic program.
	Job: The course relates to my current job responsibilities or company's line-of-business.
Social motivation	*Connect:* I am interested in connecting with other students interested in this topic.
	Friend: I have friends taking this course.
Engagement	*Lecture:* Number of lecture videos watched
	Forum: Number of forum posts
	Quiz: Number of quizzes completed
	Assignment: Number of assignments completed
Retention	*Retention:* Number of days between the start of the MOOC and the last day of activity by the student

Data Analysis Procedures

The purpose of this study is to illuminate the theoretical relation underlying student motivation, engagement, and retention in a MOOC. In the present study, extrinsic motivation, social motivation, and engagement are fully latent; i.e., variables not directly observed but which can be measured by observed indicators (MacCallum & Austin, 2000); they are measured by multiple indicators, whereas intrinsic motivation and retention are each measured by only one indicator. We used structural equation modeling (SEM) for data analysis, which is a powerful approach to examine the relations among latent variables (Kline, 2011). Specifically, we used robust mean- and variance-adjusted weighted least squares estimation (WLSMV), implemented in Mplus 7, to estimate the model, given its robustness to deal with non-normal and categorical data (Muthén & Muthén, 2012).

Model fit was evaluated using several prevailing indices (Hu & Bentler, 1999). Different indices reflect various aspects of model fit. According to Hu and Bentler (1999), the root mean square error of the approximation (RMSEA) value should be equal to or smaller than 0.06; a comparative fit index (CFI) value close to 0.95 or higher indicates a close fit, and values up to 0.90 indicate a reasonable fit. Further, a chi-square statistic indicates whether the proposed model is significantly different from the data. A non-significant chi-square value indicates good model-data fit. However, chi-square is sensitive to sample size and is more likely to be significant with large sample size (Fan, Thompson, & Wang, 1999; Hooper, Coughlan, & Mullen, 2008).

Results

Descriptive Statistics

Table 2 shows the descriptive statistics of the observed indicators. Skewness and kurtosis are used to evaluate the normality of the variable distributions (Glass & Hopkins, 1996). Both skewness and kurtosis values should be close to zero if the distribution is nearly normal. The two indicators, lecture and forum, had distributions that departed greatly from a normal distribution. We thus took a natural log transformation on the two variables. The transformed variables (i.e., ln(lecture) and ln(forum) shown in Table 2) had much smaller skewness and kurtosis values compared to the original variables. We, therefore, used the two transformed variables in the subsequent analysis.

Table 2. Descriptive Statistics of the Observed Indicators

	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
Interest	1	5	3.65	.954	-.366	-.269
Certificate	1	5	4.14	1.033	-1.129	.820
Credential	1	5	1.93	1.126	.990	-.055
Academic	1	5	1.50	1.000	1.986	2.947
Job	1	5	1.59	1.067	1.752	1.981
Connection	1	5	2.03	1.011	.761	-.101
Friend	1	5	1.26	.709	3.048	9.278
Lecture	0	621	40.72	34.085	2.163	15.778
Forum	0	765	1.83	12.744	32.128	1483.479
Ln(lecture)	.00	6.43	3.3012	1.08231	-.871	.126
Ln(forum)	.00	6.64	.3962	.77315	2.426	6.915
Quiz	0	5	1.87	2.166	.549	-1.489
Assignment	0	5	.74	1.388	1.875	2.422
Retention (days)	1	56	28.65	19.162	-.139	-1.584

Results of Structural Equation Modeling

The CFI value was .97, which is bigger than the recommended cut-off value of .95. The RMSEA value was .06, which is within the acceptable range. The chi-square test is significant (χ^2 = 2997.66, df. = 47, $p < .001$), which might be due to the big sample size. Overall, the model fit statistics are satisfactory, indicating the hypothetical model is supported by the current sample.

The standardized solution is shown in Figure 2. Both intrinsic motivation and retention have a single observed indicator. For the latent variables with multiple observed indicators, all the factor loadings are statically significant at a .05 level. For instance, the standardized factor loading from credential to extrinsic motivation was .798 (S.E. = .009, t = 89.328, $p < .001$). This indicates that one standard deviation unit increase of extrinsic motivation leads to .798 standard deviation unit increase of credential. The corresponding R^2 value was .637, which indicates that 63.7% of the variance in credential is explained by extrinsic motivation. This shows that credential is a good indicator of the latent variable extrinsic motivation. Notably, social motivation and extrinsic motivation are highly correlated (ϕ = .868, $p < .001$). This suggests that social motivation is related to extrinsic motivation, even though they are distinctly defined.

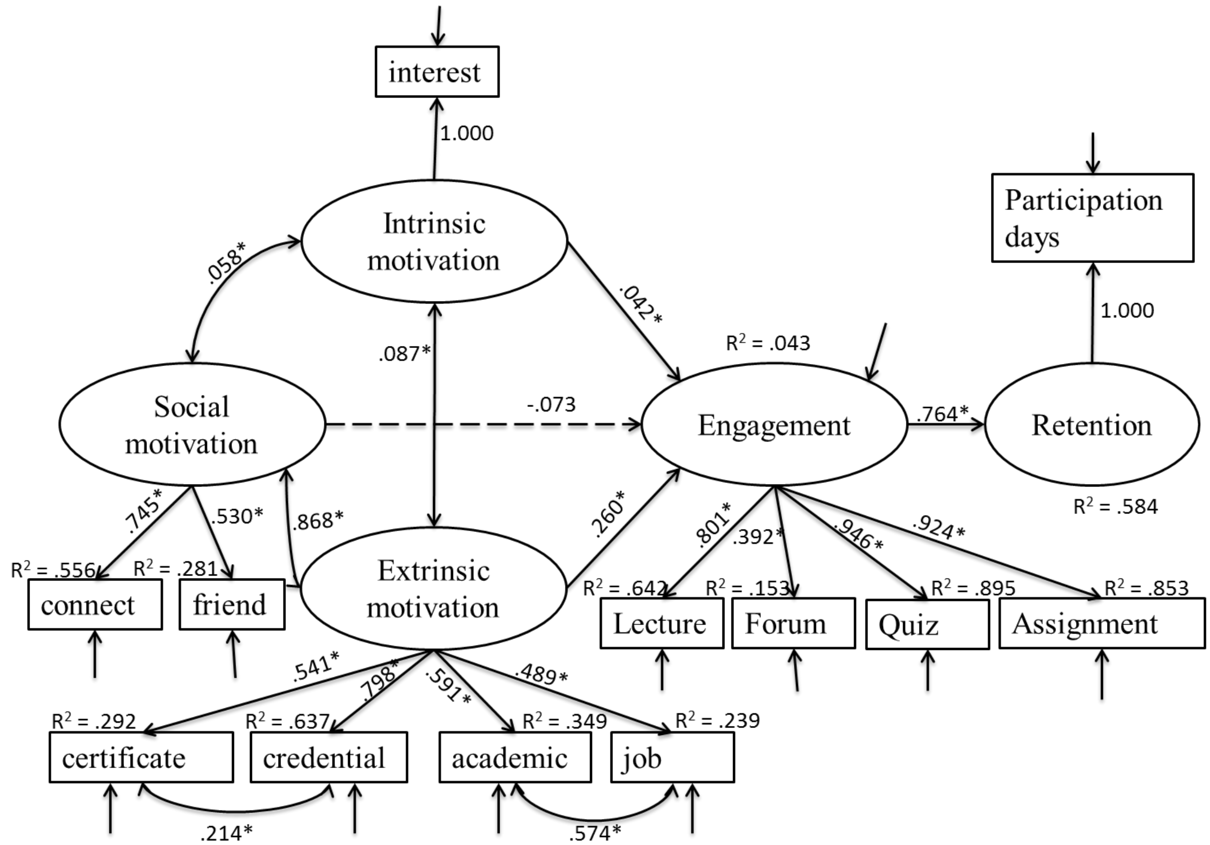

Figure 2. Standardized Estimates of the SEM Model
Note: Non-significant coefficient is indicated by a dashed arrow

Furthermore, extrinsic motivation ($\gamma = .260$, S.E. = 0.046, t = 5.622, $p < .001$) had significant path coefficients to engagement. Specifically, one standard deviation unit increase of extrinsic motivation leads to .260 standard deviation unit increase of engagement. Intrinsic motivation was also significantly related to engagement, though the relationship is small ($\gamma = .042$, S.E. = .008, t = 4.932, $p < .001$). Nevertheless, the path coefficient from social motivation to engagement was not statistically significant. The path coefficient from engagement to retention was statistically significant ($\gamma = .764$, S.E. = .006, t = 138.014, $p < .001$), which means that one unit increase of engagement leads to .764 unit increase of retention, controlling for all the other variables. The corresponding R^2 being .584 indicates that 58.4% of the variance of retention is explained by engagement.

Discussion, Limitation, and Future Study

MOOCs have raised the promise of increased access to higher education and learning. However, in contrast to fee-paying students in brick and mortar colleges, MOOC enrollees are far less likely to complete courses they register to take. Drawing on the literature of motivation, this study examined the contributions of varied forms of motivation to student engagement and retention in a MOOC at Pennsylvania State University.

We found that both intrinsic and extrinsic motivation are significant predictors of student engagement in the course. Social motivation, on the other hand, is not strongly predictive of student engagement. Furthermore, student engagement in the course predicts student retention in the course. The overall findings are consistent with the existing literature in traditional educational settings that students' motivation for learning impacts their situational engagement, such as classroom behaviors, which subsequently influence their academic outcomes (e.g., Lau & Roeser, 2002).

In general, the findings suggest that promoting student motivation and monitoring student online activities might be a way to increase MOOC retention. However, we may need to take a more sophisticated and differentiated approach to promote MOOC student motivation, given the broad range of student motivation in participating in a MOOC. While the majority of students enrolled in a traditional college are dedicated to earn a credential, MOOC students have more diverse intents. One out of four MOOC students who indicated a strong commitment to complete the course are reported to finish it (Koller, Ng, Do, & Chen, 2013). Furthermore, the completion rate among fee-paying students was even higher, which is reported to be 74% for the Coursera Signature Track classes (Koller et al., 2013). This implies that the completion rate of the highly motivated student group is much higher than the average completion rate. Therefore, it might be fruitless to promote the completion among the student group who do not want to finish the course at the first place. A more practical approach is to identify students with different intents and accommodate them to achieve their respective goals. Given that extrinsic motivation stands out as the strongest predictor of student engagement, it is reasonable for MOOC designers to provide badges, awards, certificates, or other incentives. as a means of promoting student engagement and retention. For example, the Signature Track in Coursera is a good way to promote student extrinsic motivation and foster student engagement and retention in the MOOC.

Monitoring student engagement in MOOCs provides another approach that may increase MOOC retention. Our investigation of this MOOC reveals highly skewed student engagement, as reflected in very disparate amounts of participation in student forums. Since engagement is associated with retention, efforts to design MOOCs in ways that spur engagement need to be explored. One approach might be to encourage student collaboration. Given the limited assistance from instructors or teaching assistants, building a student learning community might be the solution to increasing students' engagement in the learning process. Such work may enable MOOCs to realize not only their promise of improved educational access but also improved learning.

This preliminary study also raises a number of questions for future work. One need is to develop theory-driven instruments which can be used to explore more clearly the factors that may contribute to, or impede, students' participation in MOOCs. For example, in the current investigation, the various constructs of motivation were not equally well represented. For instance, due to the limited items in the pre-course survey, there is only one item measuring intrinsic motivation. In addition, we only found a small proportion of variance in engagement being explained by motivation. Engagement could be influenced by many other factors that have not been investigated in this study. For instance, student readiness to participate in the online courses, language barriers that a student may face, and other variables related to course design might be explored in the future. Future work is needed to address these issues.

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