Behavioral Predictors of MOOC Post-Course Development

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ABSTRACT: Massive Online Open Courses (MOOCs) have shown potential for promoting learning at scale. A plethora of studies have tapped into in-course learner behaviors to predict learner success. Yet few studies have looked to the relation between performance and engagement during the course and career development after the course. As such, the present study collected and analyzed both in-course data reflecting learner achievement and engagement in a postgraduate-level MOOC, as well as post-course career development. The goal of this research is to examine how career advancers differ from the rest of learners in terms of their performance and engagement within the course. Results showed that career advancers earned better scores and were more likely to complete the course. Career advancers also engaged more frequently with all key course components such as course pages, lecture videos, assignment submissions, and discussion forums. However, while they read the forums, they were not significantly more likely to post, comment, or vote.

Keywords: Learning analytics; massive online open courses; long-term learning development; learning outcomes; career development

1 Introduction

1.1 Background

MOOCs have been credited as a disruptive innovation in education [24] and are recognized as having the potential to help increase career opportunities for emerging fields in high demand, such as the data sciences [12]. As such, MOOCs are seen as a key opportunity to equip learners with skill sets in high demand and cater to the growingly

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diverse needs of a knowledge economy [28], that are not yet fully developed in traditional higher education systems [29].

Despite the promising outlook, few empirical studies have delved into the links between MOOCs and post-course career development. Much research in MOOCs focuses on learner achievement and engagement during the course itself, leaving the area of post-course student longitudinal development relatively untouched. It is observed that the narrative on MOOCs has shifted from overwhelmingly optimistic from 2011 to 2014 to substantially more critical in 2015 [23]. One concern is that it is not clear how well MOOCs support student learning and career development in response to changing societal needs [13]. The development of technology and scale of online education considerably outpace efforts to evaluate and understand how well it is succeeding at improving outcomes. The ongoing focus on studying MOOC completion, with longitudinal development data largely absent, obscures the possible role that MOOCs may play in the long-term professional development of many of their users.

The present study collects and analyzes three types of data reflecting both learner in-course achievement and engagement as well as post-course development in the context of a MOOC on educational data mining. This data is integrated to investigate the following question: How do MOOC learners' performance and engagement during a course relate to their post-course development in an emerging STEM field?

1.2 Related Work

In the following section, we review relevant literature and studies on the three sources of data utilized by the present study. We first introduce MOOC studies with an emphasis on learner achievement data. Then, we move on to studies that have tapped into learner engagement afforded by the availability of MOOC clickstream data. Lastly, we introduce studies emphasizing longitudinal impact on MOOC learners and present two key frameworks for thinking about MOOC post-course development.

MOOC In-Course Performance and Completion

As in traditional school and university settings, performance in MOOCs is generally measured by calculating learner assignment and test scores [4]. A total score is calculated at the end of a MOOC to determine if a student earns enough points to complete a course. The threshold for completing a course to earn a certificate is usually predefined by the course instructor [2]. Performance data in MOOCs have been used as a key metric to assess student success in MOOCs, and has served as a dependent measure in further research. Learner demographic background [10], motivation [26], prior knowledge [17], and interaction with the instructor [16] have all been studied and linked to MOOC learner performance.

However, unlike in traditional online learning platforms, many MOOC learners do not consider completing a course their primary goal [2] Although the completion rate is low relative to for-credit online courses, it is generally agreed that completion rate in MOOCs cannot be easily equated with previous learning contexts [10]. Nevertheless, performance data have served as a starting point into studying MOOC learner success.

MOOC Clickstream Data /Interaction

The availability of clickstream data allow for engineering a multitude of variables reflecting finer-grained learner engagement and revealing insights that would otherwise have stayed hidden.

Clickstream data have been used to derive measures of learner interaction with course components such as videos, discussion forums, and assignments, which have been correlated to other data. For example, Guo, Kim, and Rubin [15] used video watching logs to determine that shorter videos, the inclusion of instructor talking-head videos, and the presence of drawing-hand style instructions led to better engagement. Yang, Sinha, David, and Rose [30] looked into how social factors extracted from discussion forums influence course completion and identified predictors of completion, finding that metrics such as whether a student is a conversation initiator and a student's frequency of posting are predictive of completion. Crossley and colleagues [9] investigated the relation between discussion forum data and course completion and found out that linguistic features of student forum participation, such as cohesion, can predict course completion. Beyond this, a growing community of researchers from various disciplines have studied engagement patterns in MOOCs [18], finding that MOOC learners exhibit highly varied ways of interacting with and using the courses they enroll in.

Post-Course Development

In addition to performance and interaction within the MOOC course platform, there has been recent attention to whether a MOOC has longitudinal impact after the end of the course [22, 27], such as career advancement for learners [11]. Yet, operationalizing post-course development can take on different forms for MOOCs intended for different levels of learners, or in different domains. Before starting to measure post-MOOC development, we must first ask what MOOC learners intend to achieve after the conclusion of a MOOC and what that specific MOOC is poised to offer for the student's development. We consider this in terms of the development of individuals' careers, and the development of the communities of practice [19] that they belong to and join.

2 Method

2.1 The MOOC

We researched these issues within the context of the MOOC, "Big Data in Education" [1], using data from its first iteration, delivered via Coursera. The MOOC was created in response to the increasing interest in the learning sciences and educational technology communities in learning to use EDM methods with fine-grained log data. The overall goal of this course was to enable students to apply a range of EDM methods to answer education research questions and to drive intervention and improvement in educational software and systems. The MOOC ran from October 24, 2013 to December

26, 2013. The weekly course comprised lecture videos and 8 weekly assignments. Most of the videos also contained in-video quizzes that did not count toward the final grade.

2.2 Clickstream Data – Learner Engagement

Clickstream data from the system logs enabled the creation of variables on learners' interaction with the components of the course environment. In the present analysis, we examined student-level interaction in four categories: page views, lecture videos, discussion forums, and assignments. The clickstream log data was obtained 3 months after the official conclusion of the course (i.e. analyses on student behavior after the official course end include behavior in the 3-month period following that date).

Page views
We calculated a global variable reflecting the total number of times each student viewed a page. Additionally, we computed a variable indicating how many times a student accessed the course's syllabus page in specific.

Lecture videos
Variables representing learner interaction with lecture videos were also included. First, we computed a global variable calculating the total number of times a student interacted with any lecture video. An interaction consists of starting, pausing, rewinding, or stopping a video, as well as changing the video speed. In addition, we computed how many times a student interacted with lecture videos for each week, from week 1 to week 8 as well as during the 3 months after the course officially concluded.

Discussion forums
To differentiate types of forum interactions, we computed variables for the following forum actions: the number of times a student accessed and read a forum post, posted a new message, responded to an existing message, up-voted a message, or down-voted a message. For each of these five types of variables, we calculated the total number of actions taken during the entire duration covered by the log data, totals for each course-offering week for all 8 weeks, and a count of interaction in the 3 months after the course officially concluded.

Assignment submissions
Since the course was designed to allow students to attempt the assignments multiple times, we calculated how many times a student attempted to submit an assignment. As above, we included a global variable to cover the entire course duration, weekly counts for all 8 weeks, plus a count of submissions in the 3 months after the course concluded.

2.3 Assignment Scores and Completion Status

This MOOC contains 8 weekly assignments. For the present analysis, we calculated 8 weekly scores and a final score. According to the course policy, the final score was calculated by averaging the 6 highest grades extracted out of the 8 assignments. Students who earned a final grade of 70% or above are eligible to receive a certificate and therefore are considered to have completed the course. A total of 638 students completed this MOOC and obtained a certificate.

2.4 Post-Course Participation

Our goal in this analysis was to study the relationship between a student's interaction with the course and their later participation in the community of practice. In partnership with members of the relevant scientific societies and under the oversight of our university's Institutional Review Board, the first author was provided with a de-identified dataset linking interaction variables to indicators of post-course participation: whether the learner joined a relevant scientific society, and whether the learner submitted a paper to a relevant conference after taking the MOOC.

Society Membership Status

Learners who have enrolled in the MOOC and later joined the International Educational Data Mining Society were coded as 1 = members; learners who did not join the society were coded as 0 = non-members. The time window for joining the society was between the end of the course and Spring 2016 – an earlier preliminary analysis [27] studied individuals who joined the EDM Society in the first six months after the course, solely investigating course completion as a possible predictor. A total of 48 learners joined the society during this period.

Paper Submitting Status

During a two-year time range following the conclusion of the course in late 2013, three primary conferences in the fields covered in the MOOC offered an open call for paper submission and were held: The Seventh International Conference on Educational Data Mining, The Eighth International Conference on Educational Data Mining, and The Fifth International Learning Analytics & Knowledge Conference. Learners who submitted papers to any of the three conferences were coded as 1 = submitters; those who did not were coded as 0 = non-submitters. A total of 148 learners submitted a paper to one of these venues during this period.

2.5 Analysis

As discussed above, data were collected in three categories: 1) Course interaction; 2) Course performance and 3) Post-course community participation. Our research goal was to investigate how course interaction and performance differ between students who have shown active participation and those who did not.

We conducted a set of two-sample independent t-tests (assuming unequal variance in all cases, since this assumption was violated in almost all cases) in order to investigate this question. As this comprises a large number of statistical analyses, we controlled for multiple comparisons using Storey et al.'s [25] false discovery rate method [3]. The FDR calculations in the results were calculated using the QVALUE software package [25] within the R statistical software environment [21].

3 Result

3.1 Page Views

The results of comparisons between eventual society members and non-members on their in-course page view actions showed that eventual members made statistically significantly more overall page views, $t(47.01) = -4.00$, $q = .007$, $d = .800$, and viewed the syllabus page $t(47.01) = -2.92$, $q <.001$, $d = .569$ more frequently than non-members. Similarly, paper submitters also viewed statistically significantly more pages, $t(147.03) = -3.39$, $q = .002$, $d = .800$, and also viewed the syllabus more times, $t(147.13) = -4.01$, $q <.001$, $d = .436$, than non-submitters.

3.2 Video Watching

Eventual members performed a statistically significantly higher number of actions related to viewing lecture videos (including, as discussed above, actions such as rewinding or pausing) in total than non-members, $t(47.00) = -4.32$, $q < .001$, $d = .611$. When examined on a weekly basis, members also conducted statistically significantly higher numbers of video watching-related actions than non-members from week 1 to week 7. There were no statistically significant differences for actions during week 8 and after week 8.

Similarly, paper submitters performed a statistically significantly higher number of actions related to viewing lecture videos than non-submitters, $t(148.41) = -4.94$, $q<.001$, $d = .356$. When examined on a weekly basis, paper submitters also conducted statistically significantly higher numbers of video watching-related actions than non-submitters from week 1 to week 7. There was not a statistically significant difference for actions during week 8 and post week 8.

3.3 Discussion Forum

Results of comparisons between members and non-members on discussion forum reading actions in total and per week show that members read the forums statistically significantly more frequently than non-members, $t(47.01) = -3.65$, $q = .002$, $d = .705$. When examined on a weekly basis (table 1), members also read the forums statistically significantly more than non-members from week 1 to week 8. There was not a statistically significant difference for forum posts after week 8.

Submitters read the forums statistically significantly more than non-submitters, t(147.05) = -2.90, q = .006, d = .327. When examined on a weekly basis (table 2), submitters also read the forums significantly more than non-submitters from week 1 to week 8. A statistically significant difference was also found for forum reading occurring after week 8.

Table 1. Results of t-tests and Descriptive Statistics for Forum Reading by Society Members

Outcome	Group						
	Non-Members		Members				
	M	SD	M	SD	Cohen's d	q value	t value (df)
Total Forum Reading	2.19	20.08	32.85	58.15	.705	**.002	t(47.01) = -3.65
Week 1	.51	4.32	6.65	12.10	.676	**.002	t(47.01) = -3.52
Week 2	.33	3.37	6.21	12.42	.646	**.004	t(47.01) = -3.28
Week 3	.27	3.10	3.54	8.57	.507	*.013	t(47.01) = -2.64
Week 4	.20	2.60	3.19	8.38	.482	*.018	t(47.01) = -2.47
Week 5	.14	2.29	2.65	5.63	.584	**.005	t(47.02) = -3.09
Week 6	.19	2.78	3.15	7.90	.500	*.015	t(47.01) = -2.59
Week 7	.17	2.56	1.60	3.63	.455	*.012	t(47.05) = -2.73
Week 8	.21	3.17	4.21	12.51	.438	*.032	t(47.01) = -2.22
Post Week 8	.17	2.71	1.67	5.19	.362	.052	t(47.03) = -2.00

*q < .05. **q < .01. ***q < .001.

Table 2. Results of t-tests and Descriptive Statistics for Forum Reading by Paper Submitters

Outcome	Group						
	Non-Submitters		Submitters				
	M	SD	M	SD	Cohen's d	Q value	t value (df)
Total Forum Reading	2.16	19.68	21.49	81.20	.327	**.006	t(147.05) = -2.90
Week 1	.50	4.05	6.14	28.50	.277	*.019	t(147.02) = -2.41
Week 2	.33	3.28	3.44	16.21	.266	*.022	t(147.04) = -2.33
Week 3	.27	3.09	1.89	7.06	.297	**.008	t(147.17) = -2.80
Week 4	.20	2.59	1.44	6.42	.253	*.021	t(147.14) = -2.35

Week 5	.13	2.27	1.63	6.21	.321	**.006	t(147.12) = -2.93
Week 6	.19	2.72	2.55	11.64	.279	*.017	t(147.05) = -2.47
Week 7	.17	2.54	1.56	6.61	.278	*.013	t(147.13) = -2.56
Week 8	.21	3.17	1.66	7.14	.262	*.017	t(147.17) = -2.47
Post Week 8	.17	2.71	1.19	4.83	.260	*.013	t(147.27) = -2.57

*q < .05. **q < .01. ***q < .001.

3.4 Forum Posting, Commenting, Voting Actions, and Forum Reputation

Statistically significant differences were not found, whether assessed in total or on weekly basis, when comparing actions such as initiating a post, responding to an existing post, or voting for an existing posts either between members and non-members or between paper submitters and non-submitters.

3.5 Assignment Submission.

Members submitted assignments statistically significantly more frequently than non-members, t(47.01) = -3.75, q = .001 , d = .737. When examined on a weekly basis, members also submitted assignments statistically significantly more frequently than non-members from week 1 to week 8, though week 4 was marginally significant with a q value of 0.055. There was not a statistically significant difference in assignment submissions after week 8.

In addition, paper submitters submitted assignments statistically significantly more than paper non-submitters, t(147.12) = -5.10, q < .001 , d = .557. When examined on a weekly basis, paper submitters also submitted assignments more than paper non-submitters from week 1 to week 8. There was not a statistically significant difference for submitting assignments after week 8.

3.6 Assignment Submission

Members received statistically significantly higher final scores than non-members, t(47.01) = -3.43, q = .002 , d = .643. When examined on a weekly basis, members also received statistically significantly higher scores than non-members from week 1 to week 8.

In addition, paper submitters received statistically significantly higher final scores than non-submitters, t(147.10) = -4.35, q < .001 , d = .447 . When examined on a weekly basis, submitters also received statistically significantly higher scores than non-submitters from week 1 to week 8.

3.7 Assignment Submission

A chi-square test of independence was performed to examine the relation between course completion and post-course society membership status. Table 3 shows that the relationship between completion status and society membership status is significant, $\chi 2$ (1, N = 49952) = 116.33, p < .001; students who completed the course were more likely to join the society, by more than a factor of ten.

A chi-square test of independence was performed to examine the relation between course completion and post-course paper submission. Table 4 shows that the relation between completion status and paper submitting status is significant, χ^2 (1, N = 49952) = 176.26, p < .001; students who completed the course were more likely to submit a paper – again, by more than an order of magnitude.

Table 3. Results of Chi-square Test and Descriptive Statistics for Society Membership Status by Completion Status

Completion Status	Society Membership Status	
	Non-Members	Members
Non-Completed	49275 (98.7%)	39 (81.3%)
Completed	629 (1.3%)	9 (18.7%)

Note. $\chi 2$ = 116.33, df = 1. Numbers in parentheses indicate column percentages.

Table 4. Results of Chi-square Test and Descriptive Statistics for Paper Submitting Status by Completion Status

Completion Status	Paper Submitting Status	
	Non-Submitted	Submitted
Non-Completed	49186 (98.8%)	128 (86.5%)
Completed	618 (1.2%)	20 (13.5%)

Note. $\chi 2$ = 176.26, df = 1. Numbers in parentheses indicate column percentages.

4 Conclusions and Discussion

The present study collected data reflecting learner post-course development and related it to indicators of their participation, engagement, and performance in the course. In this study, we investigated two post-course development variables: whether a learner joined a relevant scientific community, and whether the learner submitted a paper to a relevant conference, after taking a MOOC in an emerging discipline.

Overall, career advancers (of both types) earned higher scores in the course than non-advancers. They interacted more frequently with key course components including course pages, lecture videos, and discussion forums. However, somewhat surprisingly, career advancers did not post more to the forums or participate more often in reputation voting. They did, however, access the discussion forums more often to read posts than non-advancers. These results indicate that using post-course career development indicators such as joining a professional society and submitting a paper are related to students' in-course interaction and performance.

Another somewhat surprising result is that posting to the discussion forums was not a factor differentiating career advancers from non-advancers, even though career advancers read the forums more often than their classmates. One possible reason is that content posted by some learners involves basic topics that are not associated with the types of advanced understanding and skill needed for career advancement. Another possible explanation is that many of the posts in this class were off-topic or not particularly professionally relevant, involving the color of the instructor's shirt or criticizing the video design [7]; these irrelevant posts are unlikely to benefit learners. It is possible that if these posts were removed from the data, the results would be different.

An interesting – if less surprising – result was the strong link between course completion and career advancement. Course completion, though widely adopted as a metric, has received considerable skepticism. Many have noted that completion rates are low [4], and low course completion has been treated as a crucial concern [31]. Results from the current study align to the perspective that course completion is indeed important, finding that course completion is associated with post-course development for MOOC learners. This indicates that course completion can be an important indicator of interest in assessing longitudinal learner development. Of course, despite the strong association, it is not a perfect predictor: the majority of advancers did not complete the course. This indicates that course completion is an important factor when assessing longitudinal career development, yet completing a MOOC is a prerequisite for long-term career development.

Going forward, by understanding the role that MOOCs play in career development, and understanding which student behaviors are associated with positive developments, we can work to make MOOCs more effective at promoting learner success, and help MOOCs reach the high potential attributed to them at their very beginning.

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