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Special Issue: Research into Massive Open Online Courses

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Guest Editor, IRRODL

The dramatic increase in online education, particularly massive open online courses (MOOCs), presents researchers, academics, administrators, learners, and policy makers with a range of questions as to the effectiveness of this format of teaching and learning. In early 2013, the impact of MOOCs had been largely disseminated through press releases and university reports. The peer-reviewed research on MOOCs was minimal. The MOOC Research Initiative (MRI), funded by the Bill & Melinda Gates Foundation, addressed this research gap by evaluating MOOCs and how they impact teaching, learning, and education in general. This special issue reflects the research questions and methodologies deployed by MOOC researchers over the past year and represents the current front line evaluation of how open online courses are impacting education.

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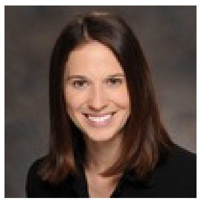
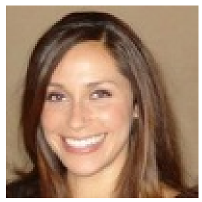
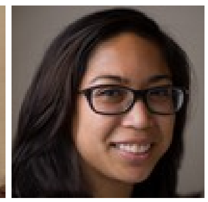
The Employer Potential of MOOCs: A Mixed-Methods Study of Human Resource Professionals' Thinking on MOOCs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Abstract

While press coverage of MOOCs (massive open online courses) has been considerable and major MOOC providers are beginning to realize that employers may be a market for their courses, research on employers' receptivity to using MOOCs is scarce. To help fill this gap, the Finding and Developing Talent study surveyed 103 employers and interviewed a subset of 20 about their awareness of MOOCs and their receptivity to using MOOCs in recruiting, hiring, and professional development. Results showed that though awareness of MOOCs was relatively low (31% of the surveyed employers had heard of MOOCs), once they understood what they were, the employers perceived MOOCs positively in hiring decisions, viewing them mainly as indicating employees' personal attributes like motivation and a desire to learn. A majority of employers (59%) were also receptive to using MOOCs for recruiting purposes—especially for staff with technical skills in high demand. Yet an even higher percentage (83%) were using, considering using, or could see their organization using MOOCs for professional development. Interviews with employers suggested that obtaining evidence about the quality of MOOCs, including the long-term learning and work performance gains that employees accrue from taking them, would increase employers' use of MOOCs not just in professional development but also in recruiting and hiring.

Keywords: MOOCs; recruitment; hiring; professional development; human resources

Introduction

Originally, much of the discussion surrounding MOOCs involved how they could be used to help students complete educational credentials. Yet recent research from the University of Pennsylvania suggests that over two-thirds of those taking MOOCs (massive open online courses) self-identify as employees. Moreover, while just 13% are taking MOOCs to gain knowledge to earn a degree, 44% are taking them to gain specific skills to do their job better and 17% are doing so to gain specific skills to get a job (Christensen et al., 2013). These findings suggest that a majority of individuals are taking MOOCs to prepare for or advance their careers. At the same time, major MOOC providers are beginning to realize that employers may be a potential revenue stream (Chafkin, 2013).

Yet employees' ability to use MOOCs to facilitate their career success and MOOC providers' ability to secure revenue from employers depends in large part on employers' receptivity to MOOCs. While the press has provided anecdotal accounts of how a few employers have incorporated MOOCs, more systematic research based on a larger pool of employers, and not just the converted, has been missing from the discussion.

Determining the extent to which taking and completing MOOCs can help individuals (particularly those who are less advantaged) advance in their careers and help fill key employer needs is critical to understanding and capitalizing on the MOOC phenomenon. To explore the current and future roles that MOOCs can play with employers, Duke University, in partnership with RTI International, conducted a quantitative and qualitative study called *Finding and Developing Talent: The Role of MOOCs (FDT)*.

Methods

The FDT project first conducted a short, multiple-choice web survey between November 15, 2013, and January 23, 2014. The survey was designed to answer four key research questions:

1. Have human resources (HR) professionals heard of MOOCs?

2. To what extent are employers using, considering using, or open to using MOOCs for recruitment?

3. How do HR professionals perceive MOOC coursetaking when making hiring decisions?

4. To what extent are employers using, considering using, or open to using MOOCs for professional development?

In addition to the survey, the project conducted qualitative interviews with a subset of 20 survey respondents. These interviews explored employer perceptions of the pros, cons, and feasibility of using MOOCs in recruitment, hiring, and professional development. The phone interviews were completed between December 12, 2013, and January 24, 2014, and participants were selected to ensure that individuals who had a range of experience with and knowledge of MOOCs (as indicated by their survey responses) were included in the interview sample. Interviews were coded using NVivo software. Differences in interview responses by the organization's use of MOOCs, consideration of using MOOCs, and ability to envision using MOOCs were analyzed and are noted whenever they occurred in the Results section of this article.

For a variety of reasons, the sample was drawn from employers in North Carolina—a state with the 10th largest population in the United States and a GDP the size of Sweden's (North Carolina State Government, 2013).[1] The FDT project obtained 706 email addresses for HR staff working for organizations with employees in North Carolina.[2] Of the 706 email addresses sent invitations to participate, 207 undeliverable responses were received, suggesting the study may have had as many as 499 "working emails."[3] Because an email address was available for multiple HR staff members at some organizations, the 499 "working email" invitations were sent to a total of 398 organizations. Figure 1 shows the distribution of these 398 organizations by completion status. A total of 103 unique organizations (26%) answered all four questions in the web survey.[4] As Figure 2 illustrates, the organizations in the study represent an array of

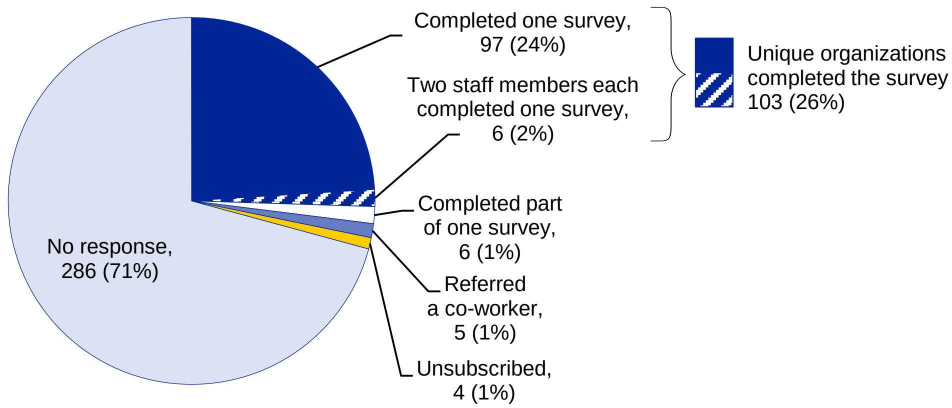
[1] There were also other reasons for focusing on North Carolina. This research received financial support from the MOOC Research Initiative. Given the timeline and budget for grantees, it was essential to focus on obtaining concrete findings for one state, with the idea that these results could then be used as the basis for developing a national study. North Carolina was selected because it is a large state that figures prominently in our nation's economy. North Carolina's population not only ranks 10th in the nation but also is growing at twice the national average. Its GDP is the 22nd largest in the world (North Carolina State Government, 2013). The prominence and ties of Duke and RTI within North Carolina were also helpful in securing the response rate needed to make a project with a small budget a success.

[2] Over 600 email addresses came from Duke's Career Services. The remainder of addresses were found through referrals or online searches. Some HR staff members were listed more than once, with their email address suffixes suggesting affiliations with multiple organizations. These individuals may have worked for more than one organization simultaneously or moved from one organization to another without their old contact information being removed.

[3] Some emails may have been filtered out by their company's software or sent directly to the junk folder sample member's email account. We do not have data on how many HR staff received the invitation in their inbox or opened it.

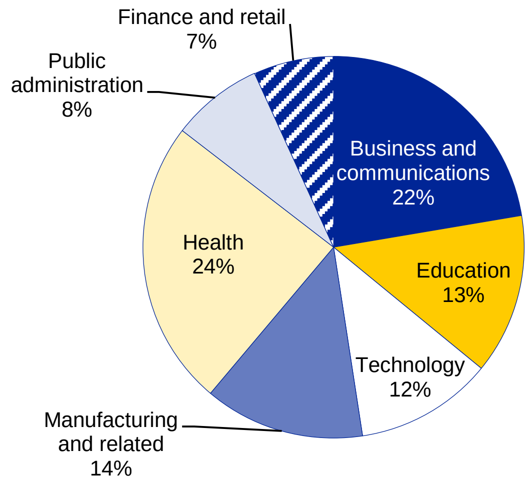
[4] Two HR staff members each completed the survey at six organizations. Sometimes the two respondents from the same organization selected different response options. In these instances, however, respondents' answers were never more than one response option apart. When there were differences in the response category selected, the higher value response was retained for the organizational analysis presented in this article.

industries. See Table 1 for more detail on the types of organizations included in each broad industry category.



NOTE: Detail may not sum to totals because of rounding.
SOURCE: Finding and Developing Talent Survey, conducted November 15, 2013–January 23, 2014.

Figure 1. Among the 398 organizations that were emailed at least one survey invitation for which we did not receive an "undeliverable" response, the number and percentage falling into each response status category.



NOTE: See Table 1 for more detail on the types of organizations included in each broad industry category. Detail may not sum to totals because of rounding.
SOURCE: Finding and Developing Talent Survey, conducted November 15, 2013–January 23, 2014.

Figure 2. Percentage distribution of the organizations that responded to the survey, by industry.

Table 1

Among the 103 Organizations Surveyed, the Number Falling into each Broad Industry Category and More Detail on the Types of Organizations in that Category

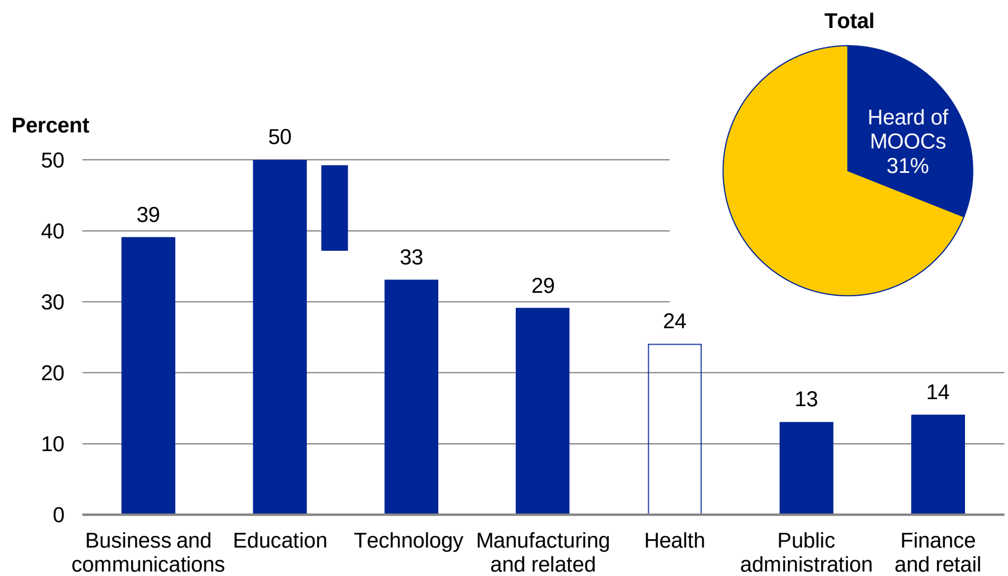
Broad industry category and type of organization	Number	Broad industry category and type of organization	Number
Business and communications	23	Manufacturing and related	14
Analytic and social services	2	Agriculture	1
Analytic services	1	Construction	1
Business services	3	Manufacturing	5
Communications services	2	Public utility	2
Consulting services	2	Transportation	5
Engineering services	4		
Legal services	2	Health	25
Marketing services	5	Health technology	6
Social services	1	Healthcare provider	8
Travel services	1	Healthcare services to	1
		Pharmaceutical	6
Education	14	Services to healthcare	4
Education services	7		
Postsecondary education	7	Public administration	8
		Federal government	1
Technology	12	Local government	5
Business software	9	State government	2
Communications technology	2		
Hardware and software	1	Finance and retail	7
		Finance	4
		Insurance	1
		Retail	2

SOURCE: Finding and Developing Talent Survey, conducted November 15, 2013–January 23, 2014.

Results

Awareness of MOOCs

As quoted in Figure 3, the first question gave a brief description of MOOCs and asked respondents if they had heard of them before the survey. Some 31% of the HR staff at the organizations surveyed answered "Yes." While this percentage may seem low, the finding is consistent with those from other surveys about the general public's knowledge of MOOCs (Brodeur Partners, 2013). Moreover, the term *MOOCs* was coined as recently as 2008 (Liyanagunawardena, Adams, & Williams, 2013), and two of the leading MOOC providers (Coursera and edX) were founded as recently as 2011 and 2012, respectively (Rivard, 2013; Bombardieri & Landergan, 2013).



NOTE: Response to the first survey question: "We are interested in your knowledge, use, and potential use of massive open online courses (MOOCs) in your human resources department. MOOCs are online courses that use social networking to bring together people interested in a particular topic and an expert who seeks to facilitate learning in that topic. Courses generally have no prerequisites, fees, formal accreditation, or required level of participation. MOOCs can be offered in many ways, but Coursera, Udacity, and edX are three of the larger providers of MOOCs that work in partnerships with universities. Some companies are also creating their own MOOCs. Had you heard of MOOCs before this survey? Yes/No."
SOURCE: Finding and Developing Talent Survey, conducted November 15, 2013–January 23, 2014.

Figure 3. Percentage of organizations that had heard of MOOCs: among all respondents and by industry.

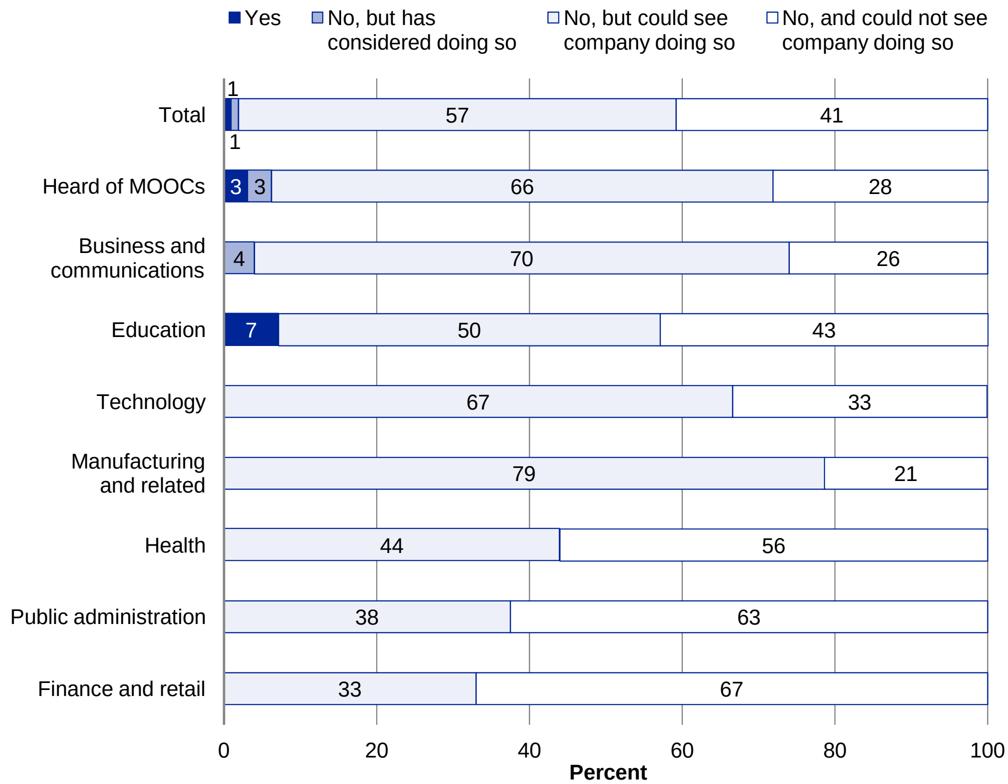
By broad industry category, half of all HR respondents from Education organizations had heard of MOOCs, as had 39% of those categorized as Business and communications organizations and 33% of those working in Technology. Awareness of MOOCs was lower (13 and 14%, respectively) among HR staff working in Public administration and Finance and retail.

Interviews revealed that those who were familiar with MOOCs at the time of the survey first learned about them in different ways. Sometimes the organization's management saw press coverage of MOOCs or thought that MOOCs might offer potential cost savings and asked HR staff to investigate this issue. Other times, employees taking MOOCs on their own started the discussion within the organization. For example, as one interviewee said,

> An employee brought [MOOCs] to our attention. [We] started discussion groups through [major MOOC provider]. . . . [MOOCs have been] a great opportunity to provide variety and content to staff. . . . [We] made our staff aware of those opportunities to tailor learning to different topics they are interested in.

Recruitment

The second survey question asked HR staff whether their organization had worked with a MOOC provider to identify and recruit individuals who have demonstrated excellent skills in a MOOC(s). As Figure 4 shows, only one organization (in Education) reported using MOOCs for recruitment, and only one additional organization (in Business and communications) reported having considered using MOOCs for this purpose.



NOTE: Response to the second survey question: "Some companies are using MOOCs to identify potential employees. For example, some MOOC participants can elect to allow their MOOC provider to share their information with interested employers. The MOOC provider then provides employers' information about MOOC participants who have demonstrated excellent skills for a fee. Has your company used MOOCs in this way? Yes/No, but has considered doing so/No, but could see company doing so/No, and could not see company doing so." Detail may not sum to totals because of rounding.
SOURCE: Finding and Developing Talent Survey, conducted November 15, 2013–January 23, 2014.

Figure 4. Percentage distribution of organizations that had used, considered using, or were open to using MOOCs for recruitment: among all respondents, those that had heard of MOOCs prior to the survey, and by industry.

The low incidence of using MOOCs for recruiting purposes is not particularly surprising because some of the main MOOC providers only started pilot-recruiting programs as recently as 2012 (Young, 2012; Jones-Bey, 2012). Moreover, by December 2013 and January 2014, edX and Udacity announced that they had abandoned these programs, with edX suggesting that they found "Existing HR departments want to go for traditional degree programs and filter out nontraditional candidates" (Udacity, 2012;

Kolowich, 2013). Consistent with edX's claim, our interviews did suggest that taking a MOOC was most often perceived as an "extra" that reflected more about potential employees' motivation and desire for continued learning than about demonstrating specific knowledge—particularly knowledge equivalent to that acquired in a traditional degree program.

Despite the low percentage of organizations using and considering using MOOCs for recruiting, once ways of using MOOCs for recruiting were described, more than half (57%) of all organizations surveyed could see themselves using MOOCs for recruitment. An even greater percentage of those that had heard of MOOCs prior to the survey (two-thirds) could envision this use. Interviews suggested that some of that receptivity may have had to do with the fact that most organizations interviewed were already using social media recruiting tools, with LinkedIn being most popular.

Nevertheless, a sizeable minority (41%) of all organizations could not see using MOOCs for recruitment. In interviews, HR staff from these organizations explained that they favored in-person methods over online ones. Others did not do any recruiting and instead relied on applications submitted through a website. Thus, organizations that seek employees who are more geographically dispersed, thereby making in-person recruiting less feasible, or organizations that have more flexibility in their recruitment practices may be more open to using MOOCs in this way.

Further industry analysis indicates that while organizations in two industry categories—Technology as well as Manufacturing and related—had not yet used or considered using MOOCs for recruiting, receptivity for doing so was high: 67 and 79%, respectively. In contrast, organizations in both Public administration and Finance and retail were more skeptical. Roughly two-thirds (63 and 67%, respectively) could *not* see their companies using MOOCs in this way. This view may reflect these organizations' lack of familiarity with MOOCs because these were the two industry categories that were least likely to have heard of MOOCs before the survey. In fact, eight out of nine respondents in these industry categories who reported they could not see their organizations using MOOCs for recruiting also had not heard of MOOCs. Greater recruitment restrictions may also help explain the more tempered reception of those working in Public administration.

Interviewers also probed about the types of hires for which MOOCs might be particularly helpful in recruiting. Respondents viewed using MOOCs to recruit for jobs that required a broad range of skills or experience as challenging. "[We do] specialized recruiting. One course is not critical; [It's] really experience level." The need for multiple factors in considering whom to recruit was also noted. One such interviewee indicated that a MOOC course was not enough to identify a promising candidate. "We don't hire many entry level [employees] that a [MOOC] completion certification would merit. . . . I can't see [our company] today saying that 'This person completed this certificate [so] let's contact them for this job.'"

On the other hand, some interviewees thought MOOCs could be particularly useful in recruiting if they provided specific technical training in high-demand areas where potential employees were hard to find. As one interviewee explained,

> [we have thought about using MOOCs for recruitment] because primarily we look for people with computer science degrees to succeed in roles here, but now with competition the way it is, it's difficult to recruit experienced individuals. We are looking for creative ways to do things.

Another similarly indicated,

> This is a tight market. We rely on software developers that fit our culture and I expect that our need will only increase as we continue to grow and change to a more software based company. . . . Any tactic that we could use to get our name to talented developers would be useful.

For the potential of MOOCs in recruiting to be fully realized, HR staff highlighted three needs. First, they wanted to be confident that the MOOC taught the specific skills needed. As one respondent related, "[Using MOOCs would be dependent on] the right test and curriculum to pull people. A lot of stuff we do is for researchers and techs, [so needs are pretty specific] in terms of skill sets." Similarly, another indicated,

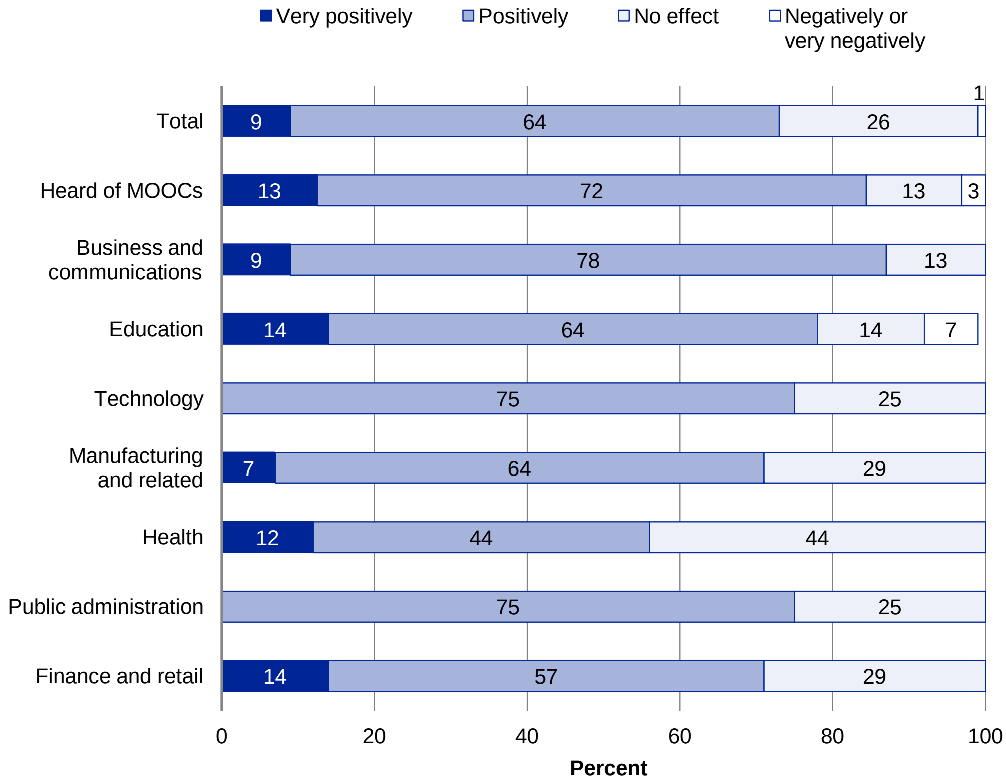
> We have a really hard time recruiting engineers and software developers. . . . We are looking for [x programming language] expertise . . . that is pretty attractive. [I could see us using MOOCs for recruiting] if they have the specific courses we are looking for.

Second, staff who were interviewed wanted evidence of learning so they could trust that a potential hire who had completed a MOOC course had the skills he or she claimed to have. Third, and relatedly, using MOOCs for recruiting would be particularly appealing if MOOCs could make it easy to find and recruit the candidates with the skills needed rather than having to rely on traditional methods of reading through resumes.

Hiring

Yet recruiting is just one part of filling an employer's workforce. Some employers do not use recruiting at all, while others fill only some positions through recruiting. Whether candidates have been actively recruited or not, employers still must decide among candidates. And oftentimes they have limited information on which to base their decision, for example, a cover letter, a resume, an interview, and a reference. It is therefore important to examine whether employers can use MOOCs to help them differentiate among applicants and to identify better potential employees. If they can do so, taking and completing MOOCs is likely to become even more appealing to those seeking new jobs.

For these reasons, the third survey question asked HR staff to rate how potential employees taking MOOCs relevant to their potential job function would be perceived in hiring decisions. As Figure 5 shows, organizations were receptive to MOOCs when it came to hiring. Specifically, 9% viewed MOOCs very positively, and nearly two-thirds (64%) viewed them positively. Among those that had heard of MOOCs, those percentages were even higher. Some 13% reported very positive views, and 72% reported positive views.



NOTE: Response to the third survey question: "Some prospective employees are noting MOOC courses they have completed when applying for jobs. If the MOOC course completed was relevant to the potential job function, how would your company view such coursetaking in hiring decisions? Very positively/Positively/No effect/Negatively/Very negatively." Detail may not sum to totals because of rounding.
SOURCE: Finding and Developing Talent Survey, conducted November 15, 2013–January 23, 2014.

Figure 5. Percentage distribution of organizations that had the following views of MOOC coursetaking in hiring decisions: among all respondents, those that had heard of MOOCs prior to the survey, and by industry.

No respondents viewed MOOC coursetaking in hiring very negatively, and only 1% viewed such coursetaking negatively. (Not surprisingly, this one HR respondent who had a negative view could not see his or her organization using MOOCs for recruitment either.)

Some key differences emerged in employers' views about using MOOCs in recruiting and hiring when comparing responses across MOOC experience levels and industries. However, differences tended to vary within a range of neutral to very positive responses.

Both the one organization that reported using MOOCs in recruiting and the one organization that had considered doing so viewed taking a MOOC positively for hiring purposes. And of the 59 organizations that could see their organization using MOOCs for recruiting, 87% viewed MOOCs positively or very positively in hiring. Even among the 42 organizations that could not see their organization using MOOCs for recruiting, 53% still perceived them positively or very positively for hiring, and 45% viewed them as at least neutral.

Examining responses by industry revealed particularly positive views by organizations in Business and communications: They were most likely to view MOOCs as either very positive or positive (87%), followed by Education (78%), Technology and Public administration (each 75%), and Manufacturing and related and Finance and retail (each 71%). Health organizations were less receptive, with a majority (56%) reporting a very positive or positive reaction, and the remaining 44% reporting that such coursetaking would have no effect.

Interview responses suggest that positions in Health and other industries that require using specialized equipment may be less receptive because, as one HR staff member explained, his or her organization's positions require extensive lab experience, which necessitates in-person training not deemed possible through MOOCs. Organizations that have less flexible hiring practices may also be prevented from considering MOOC coursetaking. A representative from one such organization reported that MOOC coursetaking would have no effect on hiring decisions until there was a mandate from management to consider MOOC coursetaking in hiring.

In thinking about the role that MOOC coursetaking may play in hiring, it is important to understand how such coursetaking is perceived compared with taking courses in other types of learning environments. HR staff stressed that traditional credentials were still the standard measure of skills rather than MOOC completion,[5] and they were less likely to view MOOC coursetaking as demonstrating specific know-how.[6] Yet because MOOCs are not seen as a prerequisite for hiring and usually do not provide college credit, HR staff tended to perceive MOOC coursetaking as a sign of positive character traits such as dedication and motivation. Specifically, potential hires who had taken MOOCs were seen as willing to continue learning on an ongoing basis and stay "up to date" in their field. They were also seen as having "drive and ambition" and as wanting "to do more

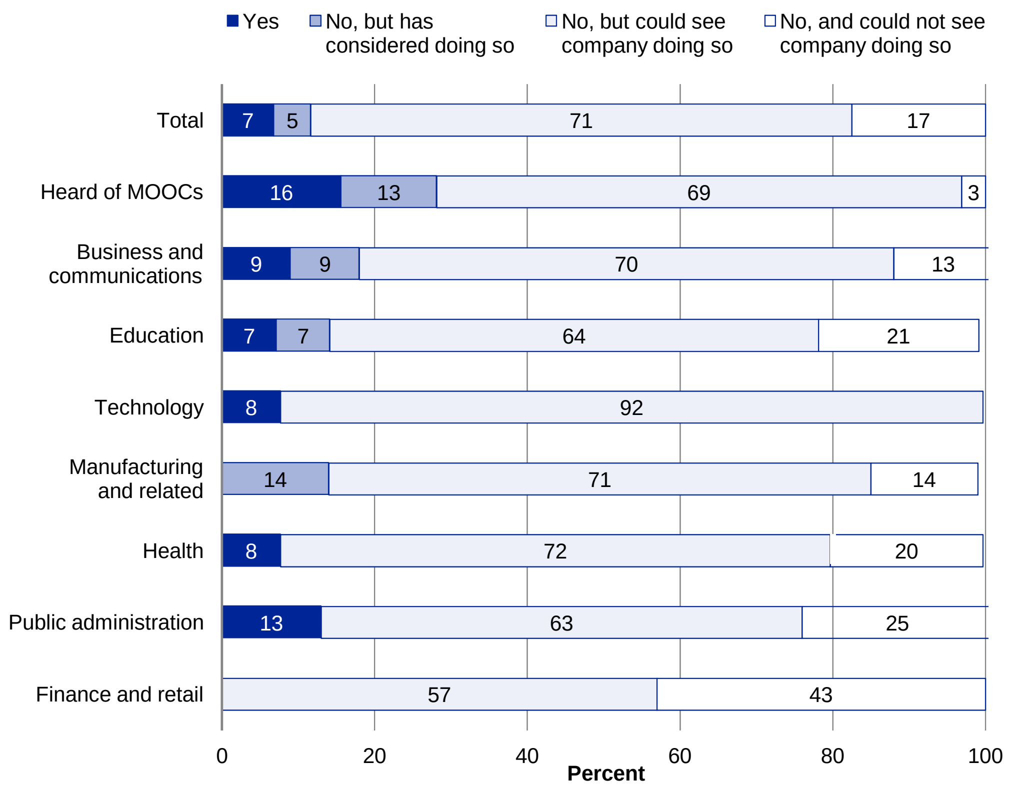
[5] This is also what edX reported (Kolowich, 2013).

[6] Nevertheless, as a couple of respondents noted, this reluctance is because MOOCs are "relatively new." These respondents suggested that this view may change if MOOCs are more rigorously evaluated to demonstrate long-term learning and behavior gains—particularly among the organization's current employees. And if MOOC completion could be seen as evidence of learning that would be an improvement over a resume, particularly for potential lower-level staff who may not have higher education credentials. One respondent explained that applicants' resumes often stated that they were familiar with basic software, but after they were hired, it became clear that they were not really proficient. He thought it would be great if MOOC completion could "verify they know what they are doing. Then we could say, 'Here is a resume with [*sic*] someone who knows something.' . . . That would help set that person apart."

for themselves, to develop themselves." In sum, while MOOC coursetaking was not sufficient to influence a hiring decision by itself, it still tended to be perceived as a "plus factor" when evaluating personal attributes.

Professional Development

The final survey question asked respondents about their organization's use or openness to using MOOCs to help existing employees learn new skills and advance in their professional development. Figure 6 shows that about 7% of organizations had already used MOOCs for professional development, reflecting somewhat early adoption of this practice considering that two of the largest MOOC providers were founded in 2011 and 2012, respectively (Rivard, 2013; Bombardieri & Landergan, 2013). An additional 5% indicated that their organization had considered using MOOCs, and another 71% could see their organization using them. Among respondents who had heard of MOOCs prior to the survey, receptivity for their use in professional development was nearly universal: Only 3% indicated that they could not see their organization using MOOCs for this purpose. These results highlight that there is great interest in, and a large potential market for, using MOOCs in this way.



NOTE: Response to the fourth survey question: "Some companies are using MOOCs created by universities or employers to help existing employees learn new skills and help with their professional development. Has your company used MOOCs in this way? Yes/No, but has considered doing so/No, but could see company doing so/No, and could not see company doing so." Detail may not sum to totals because of rounding. SOURCE: Finding and Developing Talent Survey, conducted November 15, 2013–January 23, 2014.

Figure 6. Percentage distribution of organizations that had used, considered using, or were open to using MOOCs for professional development: among all respondents, those that had heard of MOOCs prior to the survey, and by industry.

Different industries responded with varying levels of enthusiasm. Of the seven organizations that had already used MOOCs for professional development, two were in Business and communications, two were in Health, and one each was in Education, Technology, or Public administration. All of the companies in Technology were at least open to using MOOCs for professional development. The Finance and retail sector was least receptive, with three such organizations (43%) reporting that they could not see their company using MOOCs for professional development.

Interviews suggested that organizations that were using, considering using, or could see their company using MOOCs for professional development tended to be using other online (as opposed to in-person) training more often than organizations that could not see using MOOCs for this purpose.

Pros and cons for employee use.

Interviewees noted multiple pros and cons for employees using MOOCs for professional development. A key benefit concerned giving employees the ability to engage in their own development, allowing them "to take what they want," give them "goals to work on," and help increase their "self-motivation." MOOCs also enabled employees to take a "refresher course" or "stay up to date" in their field if they had been out of the traditional education system for a while.

Another benefit to using MOOCs for professional development had to do with enabling employees of all levels to advance in their careers. "Anyone could benefit from this if they had something they wanted to develop." Another respondent agreed, "[Taking MOOCs] could be applicable to everyone. Low-level support staff [could take] classes on how to be more organized and have better time management . . . all the way up to higher level employees that [*sic*] want to learn about networking."[7]

At the same time, other respondents felt that MOOCs would be less appealing to employees with lower levels of education. While HR representatives did not think that employees who already had a college degree placed importance on whether they could receive college credit for MOOCs, respondents did think that employees without higher education credentials might prefer to spend any professional development time in courses that could help them earn credit toward a degree.[8] Similarly, they believed those in jobs with continuing education requirements may be less inclined to take additional MOOCs—unless taking those MOOCs could count toward such requirements.

The online nature of MOOCs was seen as both an advantage and a disadvantage. The fact that taking a MOOC does not involve "a huge commitment to leave and go somewhere [like a college, a conference]" was viewed as a benefit, particularly for workers with families. Needing only an Internet connection to access the material was also viewed as especially beneficial for employees who traveled or worked remotely and therefore had a harder time accessing in-office professional development. Yet HR staff also noted that poor or limited Internet access could constrain access for some

[7] While MOOCs currently tend to focus on more academic subjects, the technology and method behind MOOCs would allow courses to be taught on these topics.

[8] While some MOOCs do offer college credit, thus far there have been very few MOOC coursetakers who have tried to get credit (Kolowich, 2014). This may be due in large part to the fact that studies show that 65 to 75% of MOOC coursetakers already have college degrees (Hill, 2013; Christensen et al., 2013). MOOCs might become more appealing to this population if receiving college credit becomes more commonplace.

employees. Also, employees who are accustomed to a classroom setting or more interpersonal interactions might find it more difficult to persist in MOOCs.

MOOCs' flexibility was also a pro and a con. On one hand, HR staff discussed how "It's certainly easier for the user. They can access training materials and information at their convenience." On the other hand, one HR representative explained, "When you have more flexibility then there is more difficulty in making deadlines and taking deadlines seriously. There could be less engagement than there could be in a more structured program."

HR interviewees indicated that one possible solution for ensuring that the online nature and flexibility of MOOCs held employees' interest, as well as resulted in greater accountability and completion, was to have employees take the same MOOC at the same time as a cohort. Some organizations were already doing so formally, others had employees who had taken the initiative to form groups, and others had heard that a cohort model had worked well at other organizations.

Pros and cons for employer use.

HR staff also noted multiple pros and cons for employers using MOOCs for professional development. The potential for using existing MOOCs to fill needs was one theme that they discussed. HR representatives appreciated the fact that MOOCs allowed them to expand the breadth of offerings their organization could provide. As one HR representative said, "I don't think you can have too many options to take and choose from. If anything, [it's] always helpful to have something available at work." Organizations with a range of highly technical skilled employees found it especially hard to accommodate any one particular skill in a cost-effective manner. Thus, they felt MOOCs could help fill those gaps for specific demands. Still, HR staff also noted that MOOCs could not fill all training needs and stated, "[Some courses] aren't going to be very well done in an online education [setting]." Certain training had to be "hands-on" and "more interactive to allow for clarification and [ensure employees] understood the material."

HR professionals also considered the low cost of taking MOOCs as an advantage when thinking about using them for professional development, but this advantage was counterbalanced by the potentially high labor cost incurred for employees taking MOOCs during their work day. The fact that MOOCs are free was appealing because, in the words of one respondent, professional development is something that can be set aside when "the budget gets tight." Similarly, another respondent highlighted the fact that because MOOCs are free, they would be a way to help their organization continue to provide professional development during a "budget crunch." Yet while signing up for a MOOC is technically free, employers were starting to grapple with whether employees would take MOOCs during their work day or on their own time. The labor costs of more highly compensated employees taking semester-long MOOCs during their work day are not inconsequential. If such labor costs were to be incurred, organizations would want more evidence that the course was well taught and had a lasting impact.

HR staff felt that obtaining such evidence was currently difficult. Though several noted that MOOCs are largely taught by faculty at top universities and suggested that the content should therefore be of high value, the newness and online nature of MOOCs still made some wonder about their actual quality.

Finally, HR departments also reported that MOOCs offered by top universities as part of professional development could have positive spillover effects for recruitment and employee retention. A few organizations noted that they wanted to be seen as an "employer of choice" to talented recruits and potential new hires more broadly. They believed that highlighting the availability of professional development using MOOCs taught by prominent university faculty could help them recruit excellent candidates, and particularly job-mobile Millennials—who they claimed tend to be especially interested in training that will help them advance wherever their career takes them. And another HR staff member's comments suggested that MOOCs might contribute to the retention of current employees, because MOOCs could enable organizations to provide professional development opportunities to employees at all levels, which would help all employees "know they are valued."

Desired MOOC content.

Interviewers also asked respondents about the type of MOOC content that would be most valuable. Three broad areas were discussed: basic computer skills, soft skills in developing management and leadership, and highly specialized training such as software development.

The need for professional development in basic skills like Excel and Powerpoint was least commonly noted. And one HR interviewee felt the market for this type of training was already crowded with companies providing good systems to track progress in these subjects. Access to these types of trainings, however, tends to cost money, and thus free alternatives may be attractive to smaller companies with fewer professional development dollars.

There was greater interest in MOOCs focused on soft skills like "leadership," "management," "dealing with customers," and "account management." One representative who initially could not envision his organization using MOOCs for professional development said after he learned more: "I really didn't understand [how MOOCs could work for professional development]. Now I feel like if I can find courses about leadership or management then I'd love to have the guys in office take part in that." Another stated: "Management . . . is an area we are trying to grow and improve . . . [and that] employees want to develop." Other HR departments were weighing whether it made sense to develop such courses in-house. As one HR staff member said,

> Teaching soft skills . . . there is only a certain amount of content we could teach, but if we had something more

> convenient for people . . . from another company or course that could teach it, that would be beneficial.

In sum, while the sizeable number of employees interested in leadership and management could make it cost effective for larger organizations to develop such trainings internally, if quality MOOCs could provide the same or better information, that would be of interest to a range of organizations—particularly those with smaller professional development budgets.

Using MOOCs for highly specialized technical training was also of strong interest. As one HR representative explained, "We have a small internal training and HR staff. We're only going to be able to deliver so much content. We know we're not going to be the subject matter experts." And unlike more soft-skill management and leadership classes, HR staff noted that outside professional development companies tended not to focus on specialized topics with limited pools of interested parties. As a result, employees were largely forced to rely on more expensive conferences and brick-and-mortar institutions for such training. MOOCs, with their broad geographic reach, were seen as potentially able to fill this gap. Specialized technical needs noted by respondents included a range of skills: analytics, technology, construction management, engineering design, blueprint design, and mental health/identification of mental illness.

Desired MOOC course length.

MOOCs vary in course length, but the current preference is toward courses that run for about 6 weeks (Anders, 2013). When HR staff were asked about the course length that would be ideal if MOOCs were to be used for professional development purposes, a variety of time frames were given: "no longer than 10 weeks," "7 to 8 weeks," "no more than 6 weeks," "4 to 6 weeks," "1 month," and "2 weeks." Those who reported they could not see their company using MOOCs for professional development tended to indicate that professional development courses needed to be even shorter: "1 week," "5 days," and "half a week." Other HR representatives noted that course length should be driven by course content. The desired workload for courses was also mentioned. One respondent felt courses should not require more than 5 to 10 hours of work per week or they would feel like a part-time job on top of the job employees already have.

Ways to make MOOCs more useful for professional development.

Lastly, interviewees were asked what they needed in order to make MOOCs more useful in professional development.

To begin with, for employers to encourage their employees to use MOOCs for professional development, and especially if employers are going to provide employees with work time to take these courses, numerous interviewees discussed the need for evidence of MOOCs' legitimacy, rigor, and quality. HR staff also wanted to know how MOOCs compared traditional courses on these measures. MOOCs' well-publicized low completion rates (Parr, 2013; Reich & Ho, 2014) gave HR staff pause as to the quality and level of student engagement in MOOCs.

In thinking about how MOOCs might be determined to be of value in a professional development setting, it is helpful to understand how traditional courses are assessed. One HR professional explained how researchers and scientists at his company learned from others in their field which specific courses taught at traditional universities or conferences were worth attending, while "for MOOCs the awareness is not as clear. Which ones are good and which ones aren't? Which ones don't have people dropping left and right?" Although the cost of a MOOC makes taking it low risk, providing highly compensated staff with the time to take a MOOC that has not yet been vetted by others in the field comes with opportunity costs.

A second need expressed was evidence of completion. Organizations wanted evidence that employees were making progress toward and completing MOOCs they were taking as part of their official professional development. Some in the professional development field are already doing this. As one respondent related, "When we work with [private company x], [course completion] automatically downloads to [the employee's] transcript and it downloads to the main system and we can track and assess." MOOC providers are heeding this call. For a small fee, providers like Coursera and edX already enable courestakers to show verified proof that they completed a course (Coursera, 2013; edX, n.d.). Coursera is also exploring the possibility of selling dashboards or analytics tools to companies looking to track employee progress in online training courses (Nadeem, 2013a). And Coursera, edX, Udacity, and others have teamed with LinkedIn in a pilot program that publicly certifies MOOC completions (Nadeem, 2013b).

But tracking coursetakers beyond completion was also important. As one interviewee stated, "I think as we continue to present this to [management], they will want to know . . . how we can assess whether or not these individuals are actually learning." And others wanted to be able to go beyond assessing the degree to which learning was retained and wanted to know if such coursetaking led to improvement in job performance. An HR staff member explained that to facilitate evaluation of behavior change, he would want information on the course's learning objectives as well as a simple, short questionnaire or observation checklist that could be given to co-workers and supervisors. His organization was already using such tools for other professional development courses. Such measures and metrics would greatly add to employers' ability to ascertain the value of a MOOC and encourage their adoption not just for professional development but also for recruiting and hiring.

Conclusion

The findings from this study suggest that the potential for employers' use of MOOCs is strong. Though MOOCs are only a couple of years old and a majority of employers are just now hearing about them, some employers are already using them or have considered using them and many more could see their organization using MOOCs. Overall, almost three-quarters (73%) viewed MOOC coursetaking positively or very positively when making hiring decisions. A solid majority (59%) of employers were using, considering using, or could see their organization using MOOCs in recruiting, and more than four-fifths (83%) reported positive views for using MOOCs as professional development tools. Yet interviews also indicated employers' need for evidence of MOOCs' quality and easy ways to verify employees' completion of these courses. From a professional development perspective, employers wanted to see assessments of long-term learning and behavioral gains.

Knowledge and use of MOOCs is rapidly evolving. In anticipation of expected changes in how employers perceive, use, and value MOOCs, the authors seek to build upon this study's findings by conducting a national study that further investigates these issues. Findings from a nationwide study can illuminate ways that employers and MOOC providers might better capitalize on the potential of MOOCs to identify prospective employees and better train and provide professional development to existing ones.

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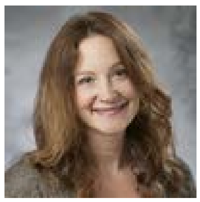
Writing to Learn and Learning to Write across the Disciplines: Peer-to-Peer Writing in Introductory-Level MOOCs



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Abstract

This study aimed to evaluate how peer-to-peer interactions through writing impact student learning in introductory-level massive open online courses (MOOCs) across disciplines. This article presents the results of a qualitative coding analysis of peer-to-peer interactions in two introductory level MOOCs: English Composition I: Achieving Expertise and Introduction to Chemistry. Results indicate that peer-to-peer interactions in writing through the forums and through peer assessment enhance learner understanding, link to course learning objectives, and generally contribute positively to the learning environment. Moreover, because forum interactions and peer review occur in written form, our research contributes to open distance learning (ODL) scholarship by highlighting the importance of writing to learn as a significant pedagogical practice that should be encouraged more in MOOCs across disciplines.

Keywords: Open learning; higher education; online learning; massive open online courses

Introduction

Massive open online courses (MOOCs) could be poised to transform access to higher education for millions of people worldwide (Waldrop, 2013). From a pedagogical standpoint, the sheer scale of these courses limits the extent of student-instructor interpersonal contact, and this leads to a central question involving how a reliance on peer interaction and review impacts student learning. Student-student interaction, once called "the neglected variable in education" (Johnson, 1981), is now recognized as a fundamental high-impact practice in education (Salomon & Perkins, 1998; Chi, 2009). Clearly humans interact via multiple modes, including in person, but also more and more frequently via long-distance digital communication such as by telephone, email, social media websites, online chats and forums, video conferencing, and blogs; all of these modes are emerging in modern pedagogies. To this end, deWaard et al. cite "dialogue as a core feature of learning in any world, whether face-to-face or digital" (deWaard et al., 2014). In fact, in face-to-face and smaller-scale online learning contexts, peer-to-peer dialogues have been shown to be critical to developing deep conceptual understanding (Chi, 2009). In MOOCs, peer-to-peer dialogues occur primarily through writing: in forums and via peer-reviewed assignments.

MOOCs, because of their scale, offer a significant opportunity for peer-to-peer interaction in the form of dialogic, networked learning experiences (Clarà & Barberà, 2013). However, also because of their scale and the diversity of student learners enrolled, MOOCs present substantial challenges in this domain (Kim, 2012). Some scholars have suggested that MOOCs limit or underestimate the importance of interpersonal engagement for learning (Kolowich, 2011; Kim, 2012; Pienta, 2013). Questions about how or whether to facilitate interpersonal engagement in MOOCs have particular importance since the majority of MOOC learners are adults (Guo & Reinecke, 2014). Research maintains that constructivist approaches to learning are especially effective with adult learners (Huang, 2002; Ruey, 2010). It is within this context that we endeavor to examine one of the key questions concerning the efficacy of MOOCs: How can interactive learning be promoted and assessed in this context?

Any exploration of this question, though, also demands an inquiry into writing. The primary mechanisms for student interaction in MOOCs occur through writing in course forums and peer reviewed assignments.[1] The act of writing has been identified as a high-impact learning tool across disciplines (Kuh, 2008), and efficacy in writing has been shown to aid in access to higher education and retention (Crosling, Thomas, & Heagney, 2007). Writing has also been shown to be effective in the promotion of learning and student success in relatively large enrollment face-to-face courses (Cooper, 1993; Rivard, 1994; Reynolds et al., 2012). Research suggests that writing instruction in online settings can provide enhanced learning experiences and opportunities for pedagogical

[1] In some cases dialogic interaction occurs verbally through video chats in such platforms as Google Hangouts.

reflection (Boynton, 2002). Moreover, across educational disciplines and compared to face-to-face dialogues in time-limited classroom settings, written, time-independent online discourse has been shown to lead to more reflective contributions by participants (Hawkes, 2001; Bernard, 2004). Research also suggests that written dialogue in online courses contributes to the development of students' critical reasoning skills (Garrison, 2001; Joyner, 2012).

Given the complex ways in which writing intersects with participant interaction in MOOCs, it is of crucial importance to examine how writing impacts the MOOC learning experience. Writing, in fact, may be a key dimension for forging intersections between MOOCs and more traditional higher education contexts. That is, amidst ongoing debates about the promise or threat of MOOCs to higher education more broadly, perhaps writing offers a point of reciprocal research, where we can learn more about the role of writing in learning across higher education contexts, from open distance learning to face-to-face settings and all the hybrid and shifting contexts in between.

Herein, we examine two separate introductory-level MOOCs: one in the humanities, English Composition I: Achieving Expertise (March 18, 2013-June 10, 2013),[2] taught by Denise Comer through Duke University and Coursera, and one in the natural sciences, Introduction to Chemistry (January 20, 2014-April 6, 2014), taught by Dorian Canelas through Duke University and Coursera. Although at first glance these courses might seem unrelated, common threads weave them together into a research project: both specifically target introductory students; focus on critical thinking and writing-to-learn to develop expertise; foster key skills for access to fields in higher education; and employ a combination of video lectures and quizzes along with formal writing assignments and informal written communication via forums. We specifically chose to conduct research across disciplines because we wanted to contribute to emerging MOOC literature that examines how disciplinarity impacts MOOC pedagogy and learning outcomes dimensions (Adamopoulos, 2013; Cain, 2014).

The main objective of this study was to evaluate how peer-to-peer interactions through writing impact student learning in introductory-level MOOCs across disciplines. Specifically, we explored the following research questions:

- How do peer-to-peer interactions through writing impact student learning in introductory-level writing and chemistry MOOCs?
- What is the impact of peer-to-peer writing on engaging students in MOOC coursework who identify as less academically-prepared and less self-motivated?
- How can peer-to-peer writing function as a metric to assess student success in MOOC delivered introductory writing and science coursework?

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[2] English Composition was funded largely through a grant from the Bill & Melinda Gates Foundation.

Our research draws on several related strands of scholarship: writing-to-learn theory, online writing theory; science, technology, engineering, and mathematics (STEM) pedagogy; and emerging MOOC research. Our research contributes to scholarship on open distance learning (ODL) by examining the role of writing as a high impact educational practice in MOOCs across disciplines.

Writing-to-learn is a pedagogy that actively involves students across disciplines in the construction of their own knowledge through writing (Sorcinelli & Elbow, 1997; Carter, 2007). Peer review makes this process not only active but interactive. Student-student and student-faculty dialogues have been shown to be critical to developing a community of scholarship for enhanced learning and deep conceptual understanding among learners (Chi, 2009; Johnson, 1981). The capabilities of MOOCs make it possible to bring this active-constructive-interactive framework (Chi, 2009) to thousands of students at one time. Indeed, emerging research suggests that MOOCs have the capacity to create unique “networked learning experiences” with unprecedented opportunities for collaboration, interaction, and resource exchange in a community of learners (Kop, Fournier, & Mak, 2011; Siemens, 2005). And, also in keeping with these findings, research has found evidence that the most successful MOOC students are typically heavy forum users (Breslow, 2013).

Given that MOOCs promise to *increase* access to postsecondary education (Yuan & Powell, 2013), we are particularly interested in how peer-to-peer interactions through writing in introductory-level MOOCs impact the learning outcomes for less academically advanced and/or under-resourced learners. Although research has also indicated that MOOCs are not yet reaching less academically prepared students (Emanuel, 2013), we endeavor to learn how less academically prepared students can best learn in these introductory-level MOOCs. Research suggests that less well-prepared students can behave more passively in academic settings, relying on memorization and imitation as strategies for learning (Mammino, 2011). This has been shown to arise at least partly from lack of comfort with the use of language, particularly if trying to communicate in a non-native language (Mammino, 2011). Research in developmental writing suggests that early emphasis on writing in a student’s academic career can improve retention and academic performance (Crews & Aragon, 2004).

Learning more about how peer-to-peer interactions through writing impacts retention and academic performance is especially critical in the context of STEM. Research suggests that the greatest loss of student interest in STEM coursework occurs during the first year of college study (Daempfle, 2004). Scholarship has found that peer interactions in introductory-level science courses, especially through writing, have in some contexts doubled student retention rates in STEM disciplines (Watkins & Mazur, 2013). Writing to learn has been used extensively in chemistry and other science disciplines and has been shown to help students confront and resolve several key barriers to and misconceptions about effective science learning (Pelaez, 2002; Vázquez, 2012; Reynolds et al., 2012). More specifically, writing with peer review has been shown to improve student performance, communication, and satisfaction even in large enrollment undergraduate chemistry courses (Cooper, 1993). We are curious to understand more about how these positive attributes of peer-to-peer interactions through writing will transfer to the MOOC environment and what impact, if any, they may have on student learning and retention in introductory science.

Methods

Our research involved intensive qualitative data coding from each MOOC using NVivo(TM) qualitative research software. Coding was accomplished by a team of 10 trained coders (doctoral students, post-doctoral fellows, faculty) during a five-day coding workshop from 11 March 2014 - 14 March 2014. The workshop was designed and led by two researchers in the social sciences at Duke University who primarily work with qualitative methods and are also authorized trainers for QSR, International for the software program NVivo. We estimate that about 175 hours of cumulative coder time occurred during the week. Below we provide more details about our methods.

Coding Protocol

Prior to the workshop, we developed a coding protocol, with the assistance of a doctoral student and postdoctoral scholar in developmental psychology. The protocol included nodes for such items as affect, length of post, attitude, learning objectives, student challenges, and elements of writing (for full coding protocol, see Appendix A).

Coding Workshop

During the workshop, coders were first led through processes to become familiar with the structure of MOOCs in general, and our study MOOCs in particular, and with important NVivo components, including data capture, import, and coding to themes. Second, coders were introduced to the pre-designed project file and node structure, and leaders oversaw use of the protocols by team members. After this step, based on coding of the same data sources by team members, leaders examined inter-rater reliability and made adjustments to the team's work. Third, coders worked individually on various data sources as assigned. Twice a day, time was taken for team discussion, and leaders were present at all times during the coding workshop to answer individual questions.

Coding Reliability

When introducing the node structure, the coding workshop leader walked all coders through each node and its planned use. Subsequently, teams of three coders coded the same two documents to the node structure. This led to assessment of inter-rater reliability and team discussion. At several points node definitions and/or structure were discussed as a whole group.

Many of the nodes are what Maxwell (2005) refers to as “organizational” or “substantive” nodes, which are more topical, descriptive, or straightforward to interpret than “theoretical” coding (which is more abstract) (p. 97). Because most of the nodes have literal definitions, with a few exceptions, to which we paid close attention, we believe little room existed for coders to differ substantially from each other on inferential coding of text.

Reliability was also established through having coders collect and evaluate different types of data from different disciplines throughout the coding workshop (for a summary of items coded, please see Table 4). This form of triangulation, called “investigator triangulation” (Denzin, 2009, p. 306), involves multiple researchers in the data collection and analysis process, and the “difference between researchers can be used as a method for promoting better understanding” (Armstrong et al., 1997, p. 597).

Finally, we spent the second half of Day Five of the coding workshop having coders review nodes in the merged file for coding inconsistencies. Various coders were given a family of nodes to open and review, using NVivo queries to consider the consistency of coding that they found.

We coded data from two different areas of the MOOCs: discussion forums and peer assessments.

Discussion Forum Data

The following data (Tables 1 and 2) provide a sense of the total discussion forum volume for these courses, from which we culled our sample. Please see Appendix A for more definitions and descriptive details.

Table 1

Discussion Forum Data, English Composition I: Achieving Expertise, 2013

Total views	520,192
Total threads	19,198
Total posts	54,479
Total comments	19,498
Total votes	42,506
Total reputation points	20,312
Number of participants posting	11,641
Number of participants commenting	5,033
Number of participants voting	6,444

Table 2

Discussion Forum Data, Introduction to Chemistry, 2014

Total views	107665
Total threads	1874
Total posts	7198
Total comments	3053
Total votes	6777
Total reputation points	2752
Number of participants posting	1645
Number of participants commenting	709
Number of participants voting	858

From this total volume, we coded a sampling of two types of discussion forum data.

Point in time (PIT) and general peer-to-peer (P2P) discussion forum posts.

We coded 35 full discussion forum threads in Weeks One, Four, and Seven of both courses. In addition, we coded 35 full threads from Week 12 for English Composition (the Chemistry course was not 12 weeks long.) We also coded general forum posts for both courses.

Top poster P2P discussion forum posts.

We captured all activities of the top three posters in each of the two courses and coded a sample of these posts. (See Table 3 for top three posters in each course and statistics.)

Table 3

Top Posters in Each Course (All Forum Activity) on Date of Coding Session

Top posters in Chemistry (number of posts)	Top posters in English Composition (number of posts)
Student A (571)	Student D (539)
Student B (133)	Student E (306)
Student C (64)	Student F (21)

Peer Assessment Data

In addition to coding data from discussion forums, we also coded data from peer assessments in each course. Students provided feedback on other students' writing for both courses. We did not code the assignments themselves.

Peer assessment sources in Chemistry.

In Chemistry, this feedback was located in a specially designated open forum for peer review of a writing assignment. Students in the Chemistry class submitted an essay on a chemistry-related topic of their choice to the peer-review tool (see Appendix B). Coursera then randomly assigned each submission to be read and commented upon by two peers according to a rubric (see Appendix C). After the first student had reviewed a peer's essay by entering their feedback as written comments, Coursera automatically populated a designated forum with the essay and anonymous peer review, whereupon any additional anonymous peer reviews would appear over time and more students could read and comment on each essay. Seven hundred and fourteen students submitted this assignment and received peer feedback. We coded evaluations on 120 submissions (16.8 percent of the total volume of submissions), randomly selected by capturing every 6th submission with correlating feedback on the Chemistry peer assessment forum.

Peer assessment sources in English Composition.

We reviewed three different types of English Composition peer-assessment data.

1. Peer feedback on a brief introductory essay, "I Am A Writer," posted to a specially designated open forum (see Appendix D). This first introductory writing activity, designed to facilitate conversations about writing among the community of learners, was conducted on the forums as opposed to through the formal peer-assessment mechanism. Thus, students could voluntarily respond to as few or as many peers' submissions as they wanted. Approximately 8,000 students posted the "I Am A Writer" assignment. We chose to capture feedback on 80 peer responses, which amounts to feedback on about 1% of the submissions. This was roughly equivalent to taking the first submission from each page of posts on the designated "I am a Writer" forum for a random sample.

2. Peer feedback provided through the formal peer-assessment mechanism. For each of the four major writing projects in English Composition (see Appendix E), students submitted a draft and a revision to the formal peer-assessment mechanism in Coursera. For each project, Coursera randomly distributed each student's draft submission to three peers in order to receive "formative feedback" according to a rubric. Then, each student's final version was randomly distributed to four other peers in order to receive "evaluative feedback" according to a rubric.

Formative and evaluative peer feedback rubrics included a series of specific questions as well as several open-ended questions (see Appendix F).[3] We only coded data from questions that seemed relevant to peer-to-peer interaction, namely,

- What did you like best about this essay?
- What did you learn about your writing/your own project based on responding to this writer's essay/project?
- What overall comments do you have for the writer as he or she moves on to project 2/project 3/project 4/beyond the course?

These peer-assessment submissions and feedback were private for students, and so in this case, as required by Duke University's Internal Review Board, the only student submissions evaluated were those from students who approved our use of these data. Throughout the course, the students provided 14,682 separate project peer assessment feedbacks. Approximately 250 students gave permission for their work to be included in this research process. We coded a random sample of the feedback provided by 50 of these students, which amounted to 342 project peer-assessment feedbacks.

This data enabled us to look at feedback on a student-by-student basis (as opposed to assignment by assignment).

3. Comments about peer feedback written in final reflective essays. Students in English Composition compiled portfolios of their writing at the end of the course. These portfolios consisted of drafts and revisions of each of the four major projects as well as a final reflective essay in which students made an argument about their progress toward the learning objectives of the course (see Appendix G). One thousand four hundred and fifteen students completed final reflective essays; approximately 250 students gave permission for their final reflective essays to be included in the research process. We coded comments about their experiences providing and receiving peer feedback in 48 of these final reflective essays.

Table 4 shows the total number of items coded for each type of source.

[3] These formative and evaluative rubrics were developed largely through a consultation with assessment expert Edward White.

Table 4

Number of Items Coded and Scores Collected

	Chemistry		English Composition		Total	
Forum postings	Sources[4]	Posts[5]	Sources	Posts	Sources	Posts
Top posters	3	85	3	209	6	294
Forums	124	1344	206	1051	330	2385
General forums	25	809	37	86	63	895
Points in time	99	535	133	768	232	1303
Week 1	29	163	36	106	65	269
Week 4	35	164	35	289	70	453
Week 7	35	208	27	169	62	377
Week 12	N/A	N/A	35	204	35	204
Peer review						
Writing assignment on forums[6]	106	370	96	325	195	695
Student portfolios	N/A	N/A	40	N/A	40	N/A
Peer evaluations	N/A	N/A	279	N/A	279	N/A
Self-evaluations	N/A	N/A	39	N/A	39	N/A

Limitations

Our research included several limitations. A primary limitation is that not all enrolled students participated by posting in the forums, so any analysis of forum posts will only include data from those students who felt motivated to post. Additional limitations include the following:

- Coders were calibrated through coding common text passages on the first day. For the rest of the coding session each piece of data was coded by individuals.
- We estimated the number of threads by multiplying 25 times the number of pages. This may be a slight overestimate, because the last page in each forum would by definition have less than 25 threads.
- Within a thread, we did not manually count the number of posts, but took the statistic from Coursera. A very small number of posts were empty or deleted by

[4] For forums, this was the number of threads collected. For peer review, the number of sources equals the number of individual documents collected. N/A means not applicable.
[5] Number of posts is the number of times someone posted to a given thread; only applicable to the forums or assignments posted to the forums.
[6] For Chemistry, this was the only writing assignment; For English Composition, this was the "I Am A Writer" assignment in Week 1.

the forum moderators as spam or containing inappropriate material. Therefore, our post count may be a slight overestimate.

- We did not review student assignment submissions. We only coded the student feedback. Therefore, our coding inferences may be limited by this constraint.

- We captured threads from the website for coding using the NCapture software from NVivo. We used the Explorer browser exclusively. However, we learned that, irregularly and unpredictably, NCapture drops a line of text at a page break in the pdf. We did not try to go back and recover these lost lines of text in our analysis.

- Although we captured the number of views of each thread, we recognize that simply by entering each thread to capture it (and thereby adding a view count), we are increasing the number of views of each of our threads. To minimize this, our procedure was to document the number of views on an individual thread before actually opening the thread. Some researcher thread views are included in the overall view counts for the courses.

- Although unlikely due to the enormous number of posts to the forums, and our limited sampling frame, we may have inadvertently coded the same post twice, because we coded to various points-in-time, and we also sampled posts from the top three posters in each discipline.

Results

After the coding was completed, we ran several queries through NVivo. Below are several of the most significant results.

Word Frequency Queries

Figure 1 illustrates the 100 most common words in weekly forums in each course. The larger the word, the more commonly it appeared in the forum.

These results illustrate visually that students were staying on topic by primarily engaging in discussions that paralleled the weekly content of the courses. For example, in Chemistry, the syllabus has the following descriptions for content in weeks six and seven, respectively:

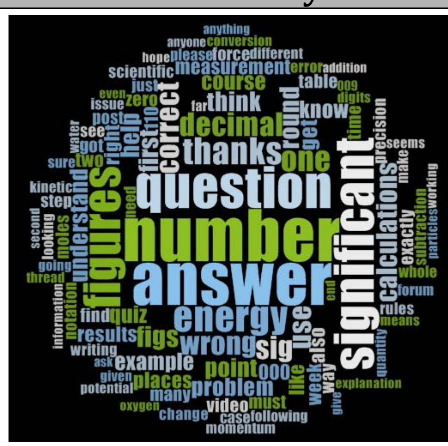
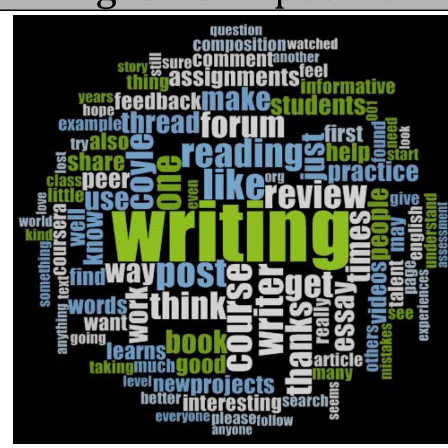
> Week 6: Introduction to light, Bohr model of the hydrogen atom, atomic orbitals, electron configurations, valence versus core electrons, more information about periodicity.

> Week 7: Introduction to chemical bonding concepts including sigma and pi bonds, Lewis dot structures, resonance, formal charge, hybridization of the main group elements, introduction to molecular shapes.

Likewise illustrating the ways in which the discussion forums stayed on topic to the course content, the syllabus for English Composition includes in Weeks 6 and 7 the following text:

> What is an annotated bibliography?
>
> Peer Feedback: Project 2 Image Analysis
>
> Sample Case Studies

Clearly, the overwhelming majority of peer-to-peer discussions in the forums for the English Composition and Chemistry courses studied herein are directly related to the course content. This observation offers a counterpoint to the observation by other researchers that "a substantial portion of the discussions [in MOOC forums] are not directly course related" (Brinton et al., 2013) and these data qualify the conclusion that "small talk is a major source of information overload in the forums" (Brinton et al., 2013).

Week	Chemistry	English Composition
1		

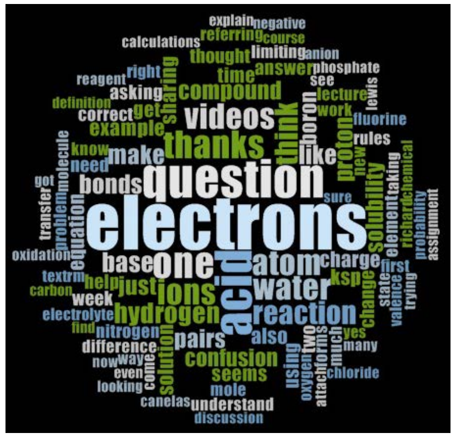
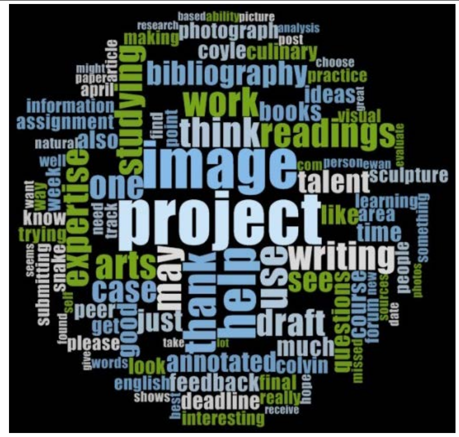
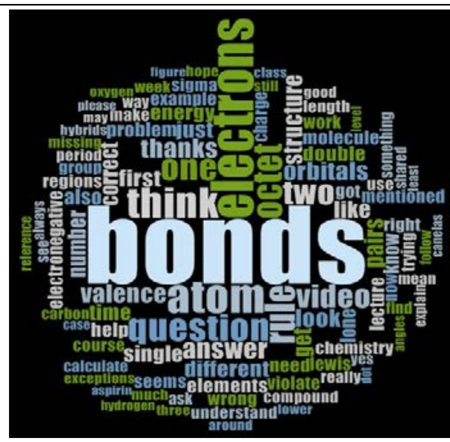
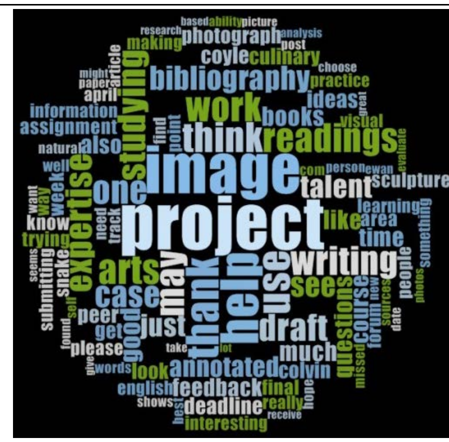
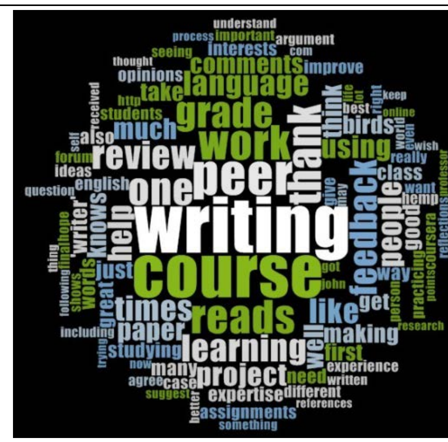
4		
7		
12		

Figure 1. Word frequency in discussion forums by week.

Discussion Forum Post Length

Table 5[7] shows post length in the forums. In general, Chemistry students' posts were shorter than those of the English Composition students. The Chemistry forum included a much higher percentage of posts that were coded as very short or short; over 90% of the posts fell into these two categories. On the other hand, English Composition forums also included many posts that were coded as very short or short (approximately 60%), but nearly 40% of the posts in this course were coded as medium or long. While Chemistry forums had about 2% of posts coded as long, English Composition had nearly 23% coded as long.

Table 5

Length of Posts in Discussion Forums

	Chemistry forums[8]	English Composition forums
Very short (less than 3 lines)	50.24%	18.72%
Short (3-10 lines)	40.00%	41.72%
Medium (11-20 lines)	7.92%	16.98%
Long (21+ lines)	1.84%	22.58%

Attitude

Attitude is well established as being critically important to learning: "In order for student-student interaction to have constructive impact on learning, it must be characterized by acceptance, support, and liking" (Johnson, 1981, p. 9). Research indicates that learners' conceptions of and attitudes toward learning have a deep impact on the efficacy of online peer assessment and interactions (Yang & Tsai, 2010).

Every post, or part of a post, if warranted, was coded as either positive, negative, or neutral (Table 6). Attitude of student writing in the forums was tracked as a function of time in the courses. Considering all coded weeks, the majority of content coded in student posts were neutral in attitude in both courses, and a relatively small percentage was coded as negative in both courses. The attitude expressed in student posts was generally more positive than negative in both courses: 2.8 times more positive than

[7] These data include Point in Time forum posts and general forum posts, but exclude data collected from top posters. We chose to exclude top posters to avoid duplication of data.

[8] Because whole posts were always coded to length, this column shows the percentage of overall posts coded to various lengths; the sum of each column is 100%.

negative in Chemistry and 3.9 times more positive than negative in English Composition.

Table 6

Summary of Attitude Coding across All Weeks in Discussion Forums[9]

	Chemistry all weeks[10]	English Composition all weeks
Positive	17.17%	27.91%
Negative	6.19%	7.02%
Neutral	76.64%	65.07%

Examples of posts coded to positive attitude:

> "I am starting to understand why I am studying on a Friday evening for the first time in my entire life. :)"

> "I appreciate all the hard work that my reviewers went to . . . thank you!"

Example of posts coded to negative attitude:

> "Go for it (un-enrole) [sic]- [two names removed]. You both know too much already and you obviously have nothing to gain from this course. You'll be doing us "stupid" students a favor."

The tenor of posts across all weekly forums was coded as slightly more positive in English Composition than in Chemistry (27% of all words coded in English weekly forums compared to 17% in Chemistry). Both Chemistry and English were coded as having roughly the same amount of negative comments (6% and 7% respectively). Note that we also endeavored to distinguish attitude from types of writing critique. One could have a positive attitude while providing constructive critique for writing improvements, for example. The greater degree of positivity than negativity in the forums suggests that the forums can provide a meaningful mechanism for establishing a

[9] This table includes data from three Chemistry weekly discussion forums (weeks 1, 4, and 7) and four English Composition weekly discussion forums (weeks, 1, 4, 7, and 12). The Chemistry course was not 12 weeks long.

[10] The sum of each column is 100%, meaning that each cell refers to the percentage of overall words coded to all weekly forums sampled.

learning community that has the potential to enhance students' learning gains and course experience.

Affect and Emotion

Affective and emotional factors are known to play a role in the success of any pedagogical practice (Gannon & Davies, 2007). Research shows that affect impacts students' response to feedback on their writing (Zhang, 1995). Affect and emotions have also been shown to be particularly important in engagement in science-related activities, and this, in turn, has been suggested as a link to improving public science literacy (Lin, 2012; Falk, 2007). Since MOOCs may be considered a pathway to increasing public understanding of scientific information and development of broad-based efficacy in essential skills such as writing, we were interested in how affect and emotion emerged in the discussion forums.

Figure 2 shows the result of queries to identify the coded affects and emotions in combined data from both courses in the weekly forums (See Appendix A for a list of all affect/emotion nodes).

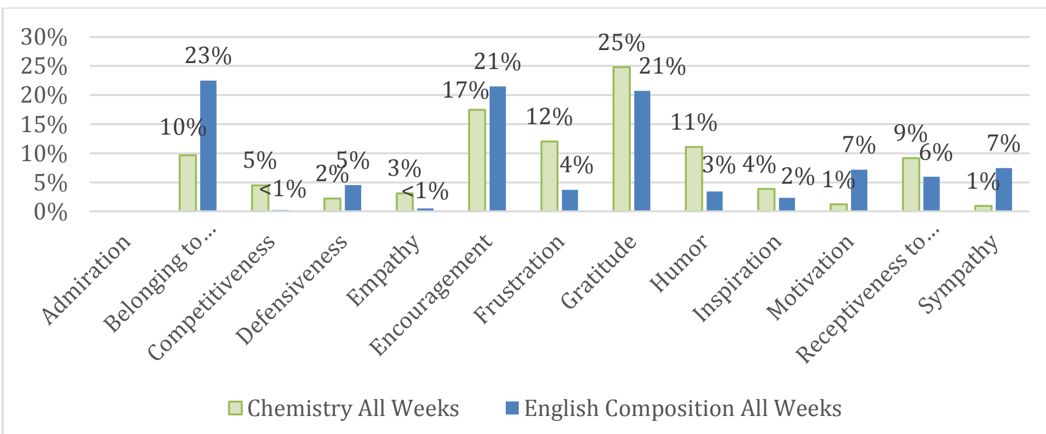


Figure 2. Percentages of posts coded to affects and emotions in weekly forums.

We coded to distinguish between attitude, as an evaluation, and affect, as an expression of feeling or emotion. Of course, students often expressed both an attitude and an affect, and in those cases, we coded to both types of nodes, but text was only coded to affect when appropriate. For example, the first quote below would be coded both to negative attitude and to the affect/emotion of "frustration", whereas the second would be coded only to negative attitude.

> Coded to both negative and frustration: "I haven't figured this one out either, or any other similar equation for that matter. I am getting really frustrated."

> Coded to negative, but not frustration: "I don't believe everyone watched and actually listened to the course instructor's direction on peer feedback. I doubt if anyone taking this course is a writing "Einstein" (genius)."

"Gratitude" and "encouragement" were in the top three of affects coded in discussion forum posts for both Chemistry and English Composition. Text coded to these affects ranged from simple phrases, such as "Thank you for your insights" or "I do think your efforts are praiseworthy," to lengthier:

> "Do not give up! It can't always be easy. Believe me or not I do some review before the quizzes and I have not yet reached 100%. Some of the questions are tricky! Try hard. Ask for help on the forums. You'll make it! :)"

In the English Composition course, "Belonging to community" was the most frequently coded affect. Text coded to this affect included the following types of posts:

> "I believe most learners here are also not expert writers, just like you and me. So let's just keep writing and keep improving together, okay?"

> "Most of the time, I feel like I'm an individual learner, but when I see the discussions, answers, and so on, I feel like there is someone who is doing something with me also, so I feel sometimes a group member."

> "I'll hope we can interact, learn and share knowledge together."

In Chemistry, "frustration," "humor," and "belonging" were frequently coded affects:

> "I am so confused about how to determine the protons and electrons that move and create different reactions. So frustrated."

> "I got strange looks from people who don't think that a sleep-deprived working single mother should be giggling at chemistry at 2am."

> "I've learnt so much from you all, and I know I can come with any question no matter how trivial."

While some writing was coded to "competitiveness" (for example, "I do not want to sound blatant or arrogant but I would expect it to be more challenging"), it was not a particularly prevalent affect. Rather, in both classes, students often expressed receptiveness to peer feedback or critique of their work.

> "I hope someone will correct anything that is wrong about what I have just written."
>
> "Oh right, I didn't notice it was in solid form when I answered! Thanks!"
>
> "But the feedback from peers, critical, suggestive and appreciative, made it possible for me to improve upon my shortcomings and garner for myself scores of three 5's and a 5.5. Am I happy? I am indebted."

Affect, Top Posters, and the General Discussion Forums

In addition to the weekly forums which were set up by the course instructors, each course also contained other forums including one called "General Discussion." Table 7 compares the affect of top posters in each course to general discussion forum posters.

In Chemistry, the top posters most strongly expressed encouragement (23% of the words coded to affect), a feeling of belonging to the community (21%), and motivation (11%). Comparatively, other posters in the Chemistry general discussion forum heavily expressed motivation (64%), with the next most commonly expressed affect being gratitude (6%). The top posters in Chemistry were also more frequently coded as being receptive to critiques (11%) than the general posters (2%).

Similarly, in English, the top posters in the general discussion forum were much more frequently coded as being receptive to critiques of their work by peers (29%) than general posters (5%). The top posters also much more frequently expressed defensiveness (20%) than general forum posters (6%). Posts in the forums most frequently were coding as expressing encouragement (20%), belonging to the community (18%), and gratitude (15%).

Table 7

Comparison of Affect among Top Posters in Each Course to Other Posters[11]

Affect Nodes	Top posters in Chemistry	Chemistry forums	Top posters in English Composition	English Composition forums
Admiration	0%	<1%	0%	<1%
Belonging to community	21%	4%	5%	18%
Competitiveness	9%	3%	0%	<1%
Defensiveness	5%	1%	20%	6%
Empathy	0%	1.87%	0%	2%
Encouragement	23%	7%	13%	20%
Frustration	0%	5%	<1%	9%
Gratitude	5%	6%	6%	15%
Humor	3%	4%	3%	2%
Inspiration	10%	2%	10%	7%
Motivation	11%	64%	7%	12%
Receptiveness to critique or comment	11%	2%	29%	5%
Sympathy	3%	<1%	8%	4%

Learning Gains and Forum Posts

One criticism of MOOCs is that assessment of student learning can be difficult when relying on multiple-choice quizzes (Meisenhelder, 2013). Many MOOCs, however, have much more versatile assignment types and answer formats available (Balfour, 2013; Breslow et al., 2013). Writing in MOOCs—whether through formal writing assignments, short-answer quizzes, or discussion-forum dialogue—can offer a strong opportunity for students to gain in learning objectives and for researchers to assess student learning (Comer, 2013). Some prior literature has even suggested that people can be more reflective when their engagement is via online writing than in face-to-face interaction (Hawkes, 2001).

Prior research reveals that through forum writing and peer assignment exchanges, students could be viewed as moving through phases of practical inquiry: triggering

[11] The discussion forums may include some of the posts written by top posters.
[12] The sum of each column is 100%, meaning that each cell refers to the percentage of overall words coded to top posters.
[13] The sum of each column is 100%, meaning that each cell refers to the percentage of overall words coded to forums.

event, exploration, integration, and resolution (Garrison, Anderson, & Archer, 2001). Discussion forums in particular offer a rich opportunity for examining student learning gains. Learning gains can be probed by analyzing student dialogue in the discussion forums to evaluate the nature and quality of the discourse. Through our coding of discussion forum posts, we were able to gain insights into student learning gains. Some students enthusiastically post about their learning experiences. Table 8 shows the percentage of discussion forum posts that demonstrated learning gains.

Table 8

Summary of Coding to Learning Gains in Discussion Forums by Course

	Chemistry forums	English Composition forums
Learning gains (aggregated)[14]	37.6%	62.4%

Some of these posts about learning gains are quite general in nature: “I don’t know about you, but I’ve already learned an amazing amount from this class!”

Others show very discrete evolutions in learning:

> “I was stuck with the idea that my introductions should be one paragraph long. Maybe I should experiment with longer introductions.”

> “And I feel comfortable enough with the chemistry, the basic chemistry, to not avert my eyes like I used to. Whenever I saw a chemical equation I just, oh well, never mind, and I’d just skip it.”

Figure 3 shows the distribution of these learning gains in Chemistry forums. When learning gains were present in Chemistry discussion-forum posts, they were frequently coded to demonstrating understanding.

Figure 4 shows the distribution of these learning gains in English Composition discussion forums. When learning gains were present, they were most often related to demonstrating understanding, but also showed significant gains in evidence of incorporating feedback. Like the learning gains in Chemistry, English Composition students also had a very low incidence of discussions about their grades (3.27% and 1.58%, respectively).

[14] The sum of each row is 100%, meaning that each cell refers to the percentage of overall words coded to a learning gains.

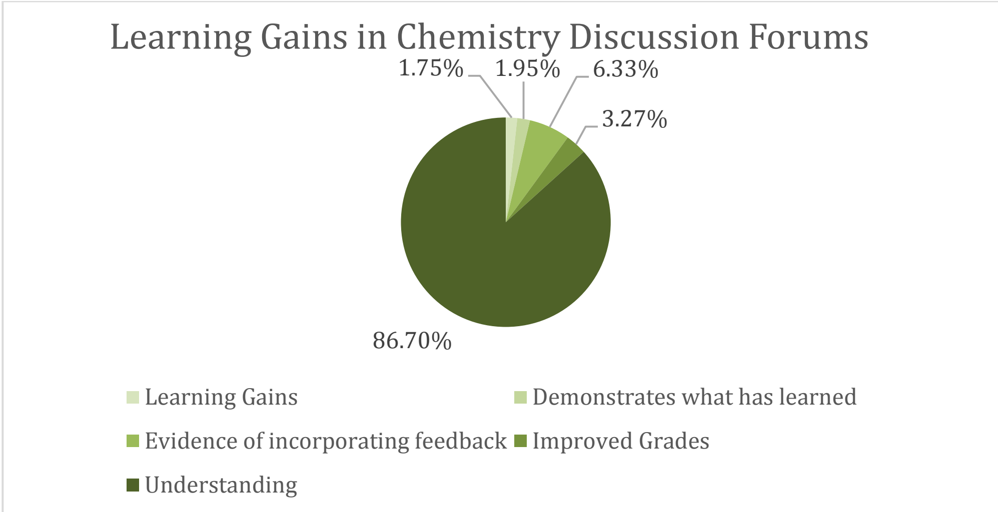


Figure 3. Coding to learning gains in Chemistry discussion forums.

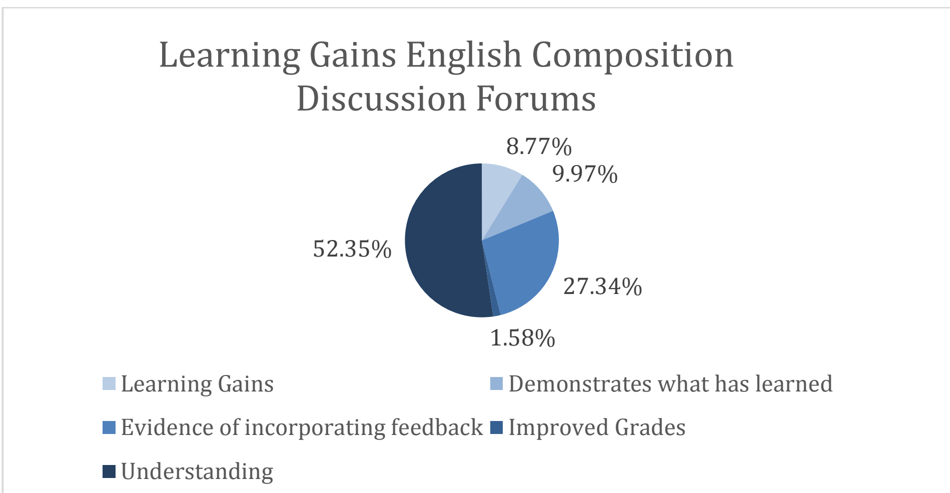


Figure 4. Coding to learning gains in English Composition discussion forums.

In both courses, very little text was coded to the "improved grades" node. Research shows that a focus on grades can be counterproductive to learning gains (Kohn, 2011). The coding results here suggest, therefore, that when students were discussing learning gains they were discussing more meaningful measures of learning gains than grades. Indeed, students posting on the forums in these MOOCs were much more focused on learning than on grade outcomes. As an illustration, one student expressed this sentiment concisely by writing, "I am not hung up on the grade I am too excited about what I learned and how I am putting it into practice and getting results."

Writing Elements in Peer Review

Enrollees' tendency to discuss more meaningful measures of learning gains in the forums also extended to their interactions through peer review. Peer review is more effective when peers focus on higher order writing elements as opposed to lower order concerns (Elbow, 1973; Clifford, 1981; Nystrand, 1984; Keh, 1990). Figure 5 shows the writing elements learners commented on in the open-ended peer review questions. For English Composition, learners commented most frequently on argument and analysis, format and style, and structure. For Chemistry, learners commented most frequently on topic, evidence and research, and plagiarism.

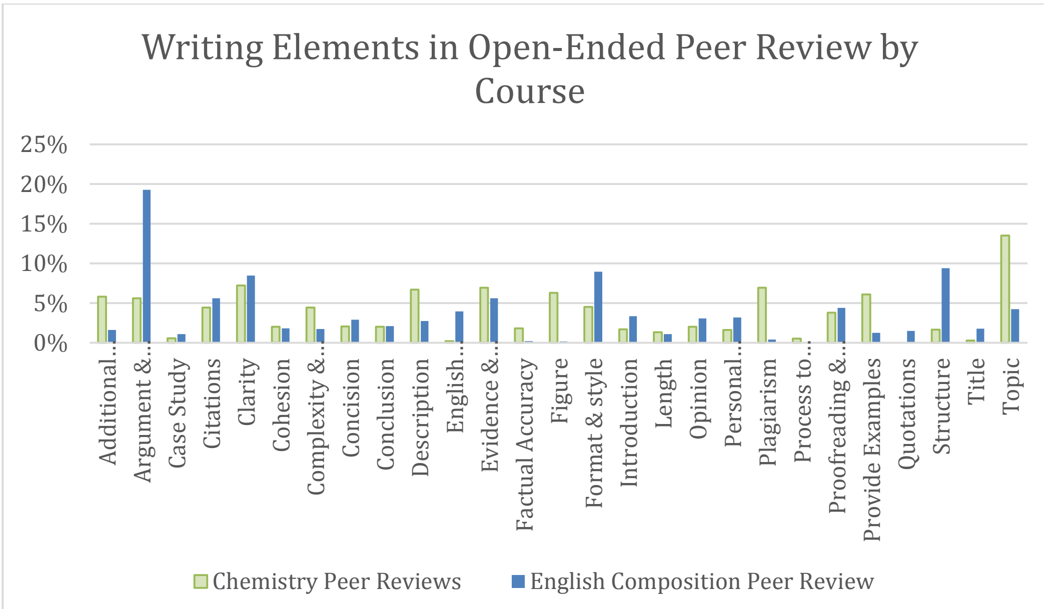


Figure 5. Writing elements in open-ended peer review by course.

The greater prevalence of peer notations about plagiarism in Chemistry is likely due to the course instructor specifically asking peers to look for plagiarism: "This is going to come up some small fraction of the time, so here is the procedure: What should you do if you are reviewing an essay that you believe is blatant plagiarism?" Suspected plagiarism was then confirmed by the instructor, who investigated student flagged work. Editorials have expressed concern that MOOC providers and faculty need to be more rigorous at facilitating academic integrity and discouraging or penalizing plagiarism (Young, 2012). Continued work should indeed be done in this area. This is especially important given that, when writing assignments are used on this scale, observations made in face-to-face settings can be magnified. For example, Wilson noted in the summary of his work about writing assignments in a face-to-face chemistry course that "Not all students submitted original work" (Wilson, 1994, p. 1019). A perusal of

Chronicle of Higher Education faculty forums reveals that plagiarism continues to constitute a challenge in all educational settings rather than being unique to MOOCs.

However, while academic honesty is of the utmost importance, it is also important to continue facilitating peer commentary based on other elements of writing, especially the higher order concerns named above. Some students expressed a negative impact from what they perceived to be too great a focus by their peers on plagiarism in the Chemistry peer review: “This peer review exercise is rapidly turning into a witch hunt. My opinion of this course has, during the past 2 days, gone from wildly positive to slightly negative.”

Type of Feedback in Peer Review

Research shows the kind of peer feedback provided impacts peers’ perceptions of the helpfulness of that feedback (Cho, Schunn, & Charney, 2006). We categorized peer feedback by type: positive, constructive, or negative. We defined positive as consisting of compliments that were not related to improving the paper; constructive comments included helpful feedback that a writer could use to improve his or her project or take into consideration for future writing occasions; and negative feedback included comments that were not compliments and were also unconstructive/unhelpful. The ratios of feedback coded as compliment:constructive:negative/unconstructive was 56:42:2 in the peer reviewed assignments and 8:90:2 in the weekly and general discussion forums.

Below are examples of text coded as unconstructive and constructive, respectively:

> “Did not read past the 3rd paragraph . . . I am sure it was interesting . . . You just did not keep my interest.”

> “Below are my suggestions as a Anglophone and an opinionated reader. . . . . Before we begin, you used the word feedbacks in the title of this thread. Feedback is the correct term. One of those annoying inconsistencies in English.”

Positive feedback in peer review.

Figure 6 shows the distribution of writing elements specifically among positive feedback in the peer review process, what we termed “compliments.” For Chemistry, compliments were most often focused on topic, clarity, description, evidence and research, and figure (learners included figures in their chemistry assignments). For English Composition, positive feedback was most often focused on argument and analysis, structure, format, and topic. Compliments were least often provided in Chemistry peer reviews to the process of assigning peer review, proofreading and grammar, and quotations.[15] Positive feedback was least often provided in English Composition peer reviews to process of assigning peer review, factual accuracy, and figure.

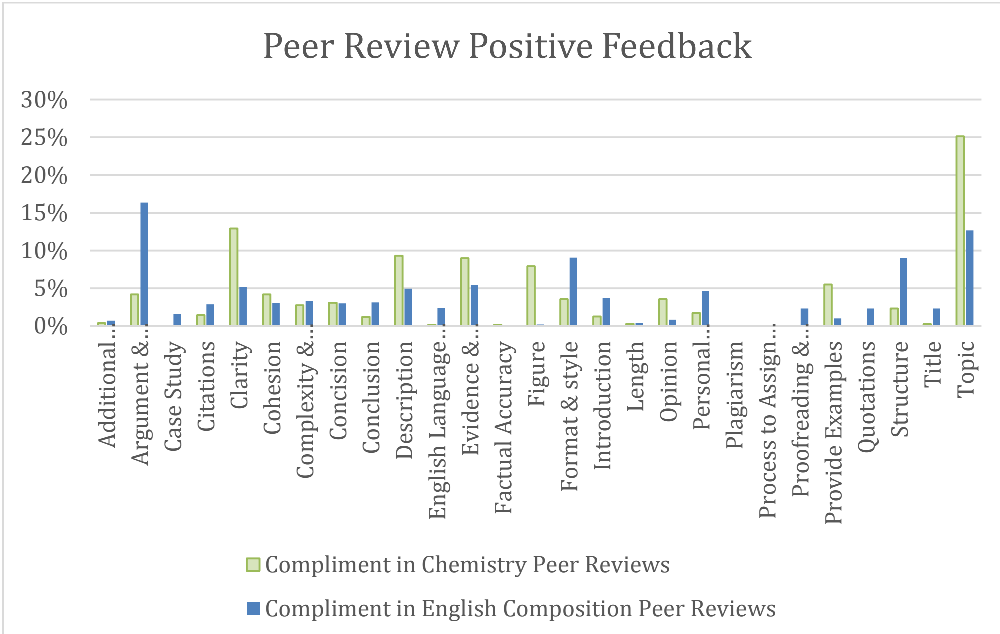


Figure 6. Positive feedback writing elements in peer review open ended questions by course[16].

Students posted positive feedback illustrated by the following excerpts:

> "Well written. Good explanations of the chemistry. I liked how it was a topic that you are clearly passionate about."
>
> "I liked your essay, it is cohesive and concise and its subject is intriguing!"
>
> "You did the great research ... and your bibliography is impressive. The introduction is brief, but sufficient, the problem you've built your text on is claimed clearly, and

[15] Compliments were also least often coded to plagiarism in both courses, but we eliminated that from the compliments because noting plagiarism is implicitly not considered a compliment. The writing element labeled Citations enables learners to comment on citation in the form of a compliment.

[16] Total distribution for each course is 100%, meaning that each percentage refers to the percentage of overall words coded to the positive feedback (or compliment) node for a given course.

> your arguments are well supported by references and quotations."

Constructive criticism in peer feedback.

Peers in English Composition were most likely to provide constructive feedback on argument and analysis, English language skills, citations, and format and style. Peers in Chemistry were most likely to provide constructive criticism on additional resources, topic, format and style, and factual accuracy. Coding frequency for both courses is shown in Figure 7.

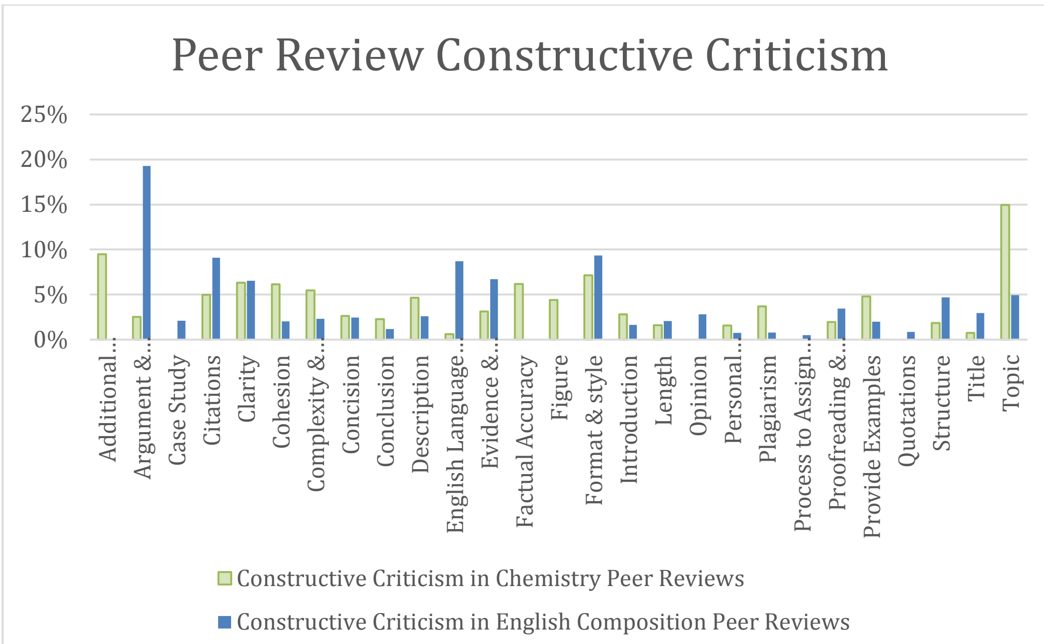


Figure 7. Constructive criticism writing elements in peer review open ended questions by course.[17]

Students posted constructive criticism such as the following:

> "... I could hear your voice among the voices of the cited books and articles, but it is not always obvious where you agree and where you oppose to the cited claim. Probably, you could sharpen your view and make your claim more obvious for your readers."

[17] Total distribution for each course is 100%, meaning that each percentage refers to the percentage of overall words coded to the constructive feedback node for a given course.

> "Just as a tip, you could have shown some pictures" of the funghi.

Unconstructive criticism in peer review.

Unconstructive feedback was defined as comments that were negative but not helpful in terms of recommending specific improvements to the student whose work was being reviewed. Figure 8 shows the distribution of unconstructive feedback in the open-ended peer reviews in each course. Peers were most likely to center unconstructive feedback in English Composition on matters of argument and analysis, clarity, and format and style. For Chemistry, peers were most likely to provide unconstructive feedback on topic, opinion, and additional resources.

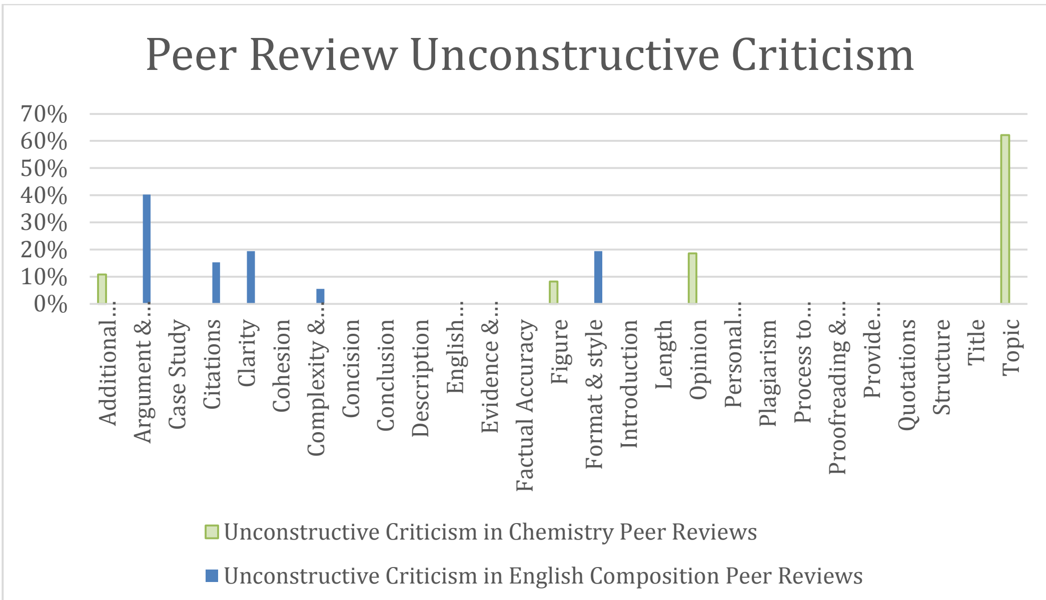


Figure 8. Unconstructive criticism writing elements in peer review open ended questions by course.[18]

Examples of unconstructive feedback included the following: "Did not read past the 3rd paragraph . . . I am sure it was interesting . . . You just did not keep my interest."

It is important to note that because we did not code the assignment submissions themselves, it may have sometimes been difficult to identify what is or is not constructive or unconstructive feedback, particularly in the case of citations and plagiarism. For instance, in some cases, peers responded to feedback as though it were

[18] Total distribution for each course is 100%, meaning that each percentage refers to the percentage of overall words coded to the unconstructive feedback node for a given course.

unconstructive, but we do not know for sure whether this feedback about citations was or was not warranted:

> "I did research and re-phrased parts of my sources into this essay with citations as is accepted practice. Did you expect me to carry out my very own experiments and post the results? I mean honestly, I am offended by that suggestion. … The only issue I can see is that the numbering of the citations went off during editing, but since all of my sources are still listed at the bottom of the essay this should not be a problem . . . It is also my work, so I would like you to retract your statement, I find it offensive."

Learning Gains and Peer Feedback

Peer feedback has been shown to enhance learning environments (Topping, 1998). Many posts in the discussion forums and peer reviews from both courses, as well as in the final reflective essays from English Composition learners, indicate that the peer-feedback process contributed to their learning gains.[19] Some of these posts about learning gains from the peer-feedback process are general in nature:

> "I found peer comments and their assessment invaluable."

> "[I have been] learning so much from all of the peer review submissions that I have decided to remain in the course just to learn everything I can learn about Chemistry."

> "Throughout the course, I valued my peer's comments on my drafts so I can improve my writings. I also learnt much by evaluating my peers' work."

Other posts show very discrete evolutions in learning:

> "I am, however, grateful for the kind parts of your review, and willingly admit to faults within the essay, although until this week, I was, like my fellows, unaware of the expected work on electron transits. By the time I did become aware of this, it was too late to make alterations! Thank you for a thoughtful review."

[19] Assignments and peer-feedback rubrics for English Composition were designed in collaboration with writing assessment expert Edward M. White.

> "Even more important bit I learned was the importance of feedback. Feedback provides an opportunity to rethink the project, and dramatically improve it."

Table 9 shows the frequency of when peer feedback explicitly expressed learning gains. The English Composition peer review rubric specifically asked reviewers to indicate what they had learned from reading and responding to the peer-writing project (see Appendix F). The Introduction to Chemistry peer rubric did not ask this. This probably accounts for why the learning gains were so much more evident in peer review in English Composition than in Chemistry.

Table 9

Learning Gains in Peer Review

	Chemistry peer review	English peer review
Learning gains[20]	2.55%	97.45%

Figure 9 shows coding for specific learning gains in peer feedback. In English Composition, peer review provided students with learning gains across four primary areas: understanding, learning through providing peer feedback, demonstrating what the person had learned, and evidence of incorporating feedback. In Chemistry, learning gains from peer feedback occurred most often around matters of understanding, demonstrating what the person had learned, and evidence of incorporating feedback. As with the learning gains in discussion forum posts, the coding shows that students are not focusing on grades, but are instead focusing on higher order concerns.

[20] The sum of each row is 100%, meaning that each cell refers to the percentage of overall words coded to a learning gains.

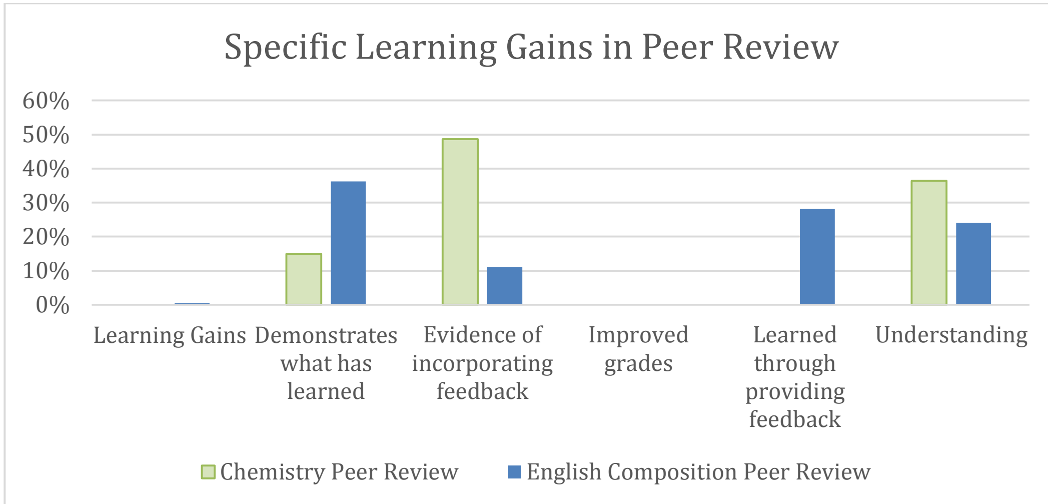


Figure 9. Specific learning gains in peer review.

Learning Gains and Student Challenges

Because we are interested in the impact of peer-to-peer interactions with less academically prepared students, we specifically looked for challenges faced by students, such as the following: lack of time or energy;[21] less academically prepared; and less or not self-directed. Interestingly, little text was coded to these nodes. For example, only one coding reference was found at the intersection of any of these challenges and learning gains. Therefore, these barriers did not come up in the forum threads that we coded in either class.

Discussion/Conclusions

We have identified several significant themes that show the importance of and impact of the peer-to-peer interaction through writing in MOOCs.

MOOC Discussion Forum Posts are Connected to Course Content

Both courses examined generated substantial student dialogues on the forums. Students in the English Composition: Achieving Expertise course tended to write longer forum posts than students in the Introduction to Chemistry course. Peer-to-peer dialogue on the weekly forums closely mirrored the content of the course described in the syllabus for that week. This shows that students are primarily discussing course content in these

[21] Lack of time or energy could be a factor associated with less academically prepared students, or it could be unconnected to that mode of student challenge.

forums and suggests that peer-to-peer writing in the forums can provide one measure of student success in a MOOC.

MOOC Discussion Forums Generally Contribute Positively to the Learning Environment in Chemistry and English Composition

Since attitude was generally positive and the top affects in the forums include belonging to a community, gratitude, and encouragement, we conclude that the forums are in general a positive space for learners to interact. This finding operated across disciplinary context, both in a natural science course and in a more humanities oriented course.

MOOC Discussion Forums Contribute to Learning Gains, Especially in Understanding

In terms of observed learning gains, peer-to-peer interaction on the forums seemed to make the most impact on enhancing and facilitating understanding. Students sought, offered, and provided tips or support from one another on the forums as a way of increasing their understanding of course content.

Peer Review Can Facilitate Learning Gains If This Possibility is Made Explicit

The disparity between the coding for learning gains in English peer reviews and in Chemistry peer reviews suggests that the English students were indicating learning gains because they were asked to do so explicitly. This suggests that faculty should encourage students to reflect on their learning gains explicitly as a way of facilitating those very learning gains.

Peer Feedback on Writing can Meaningfully Focus on Higher Order Concerns across Disciplines

Feedback on writing can be differentiated between that which focuses on higher order or lower order concerns. Effective formative feedback generally must include a focus on higher order concerns, and can then be considered an integral part of the learning and assessment environment (Gikandi, 2011). Peers in both courses focused predominately on higher order concerns, even as they were also able to focus on lower order concerns. This may be due to the peer feedback rubrics. Our data also suggest that peers will follow closely the rubric provided by the instructor. In English Composition, students were asked to focus on argument and analysis. In Chemistry, students were asked to focus on strengths, insights, areas for improvements, and plagiarism. In both cases the students were likely to adhere to the rubric guidelines.

Writing through the Forums Enhances Understanding

Since forum discussions in a MOOC happen through writing, one can extrapolate from our data that writing enhances understanding in MOOC forums. This bolsters evidence for writing-to-learn and suggests that MOOC forums are a key pathway for writing-to-learn and a key pathway for assessing student success in MOOCs across disciplines.

A Limited Group of Learners Posts to the Forums

One of our key areas of inquiry was to understand how peer-to-peer interaction through writing might impact the learning gains of less academically prepared learners. We found, however, that people posting to the forums did not identify themselves explicitly as less academically prepared. This generates questions about how many people post to the forums, and who is or is not likely to post to the forums. The total number of people who posted to the discussion forums in English Composition represents 23% of the total number of people who ever actually accessed the course (51,601); in Chemistry, the total number of people who posted to the discussion forums represents 7% of the total number of people who ever actually accessed the course (22,298).[22] Given the overall positivity of the forums, one wonders if these data indicate that the forums are only positive for certain types of people. Given that the top posters coded higher for "defensiveness" than general posters, one also wonders if there might be drawbacks to certain levels of forum participation. We did not see any significant information about student challenges in the coding data, despite looking for it as one of our coding nodes. Since interactive learning offers so much promise for these learners, and since MOOCs continue to provide the possibility of increased access to higher education, more research is needed about how to facilitate forums in as inclusive and productive a way as possible for less academically prepared learners.

The development of quality educational opportunities through MOOCs, and learning more about how peer interactions through writing contribute to student retention and learning, has the potential to make a significant global impact and increase postsecondary access and success in unprecedented ways. As we discover more through this research about how peer interactions with writing contribute to student learning outcomes and retention, we will be better positioned to understand and work towards a model of higher education that is more flexible, accessible, and effective for the great many individuals in the world interested in pursuing lifelong learning.

[22] Coursera also counts the number of people who comment on the forums, so the percentage might be a little higher for forum participation if we included this number. However, the people who comment may also be the people who post, and so counting it this way could have ended up in duplicating data.

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Apppendix A

Coding Protocol, Definitions, and Node Structure

The following information helps define our terms: Forum: A forum is the top level discussion holder (Week 1). These are created in Coursera by instructional team staff. Subforum: A subforum is a discussion holder that fall under the top forum (Week 1 Lectures, Week 1 Assignment). These are also created by instructional team staff. Thread: A thread is a conversation begun by either instructional team staff or by students. A single forum typically contains many threads covering many different subjects, theoretically related to the forum's overarching topic. Post: A post is an individual's response to a thread. Posts can be made by either instructional team staff or by students, and may be posted with the students identifying name, or may be posted as anonymous. Staff with administrative privileges may "toggle" a setting on each post to reveal the identity of students who have chosen to post anonymously. Although in theory a post is a new "top level" contribution to an existing thread (as opposed to comment (read below), many students don't pay attention to whether they are posting or commenting, and therefore, we didn't feel that we could accurately distinguish between the two. Comment: A comment is a reply to a post. Comments can be made by either instructional team staff or by students. Again, we decided not to distinguish semantically between a post and a comment, because we felt that distinguishing them was not possible in (the very common) complex web of post, response, subsequent post, subsequent response, etc.

The main page of a forum lists all the primary threads begun in that forum or subforum. If threads are begun in a subforum, they are only listed in the "all threads" area of the subforum, not in the "all threads" list of any parent forum. Subforums may themselves have subforums (which are also called subforums). At the bottom of a list of "all threads," you can read the total number of pages of threads that exist; each page contains 25 thread headings. Therefore, an estimate of the number of threads can be obtained by multiplying the number of pages by 25.

Coursera provides a number of views received by each thread, as well as the number of times a thread has been opened and read. Of course, by opening a thread to capture it for analysis, we are increasing the number of views of that thread, so we used the "views" number in our analysis with this limitation in mind.

Coursera also allows the viewer to sort by "Top Thread," "Most Recently Created," and "Most Recently Modified." We always sorted by "Top Thread" before beginning our sampling and capturing process. Top threads are defined as those that have the most posts and comments, views, and/or most reputation points or up votes on the original post that started the thread (see below). Number of posts, comments, and views certainly provide one measure of student engagement and activity. Two other related metrics exist in Coursera. Students can choose to vote certain posts "up" or "down," and are encouraged to do so to bring thoughtful or helpful posts to the attention of their peers. This simple "like" type of toggle exists at the bottom of each post or comment. Students also receive "reputation points" when their posts are voted up (or down) in the forums by other students. Specifically, "Students obtain reputation points when their posts are voted up (or down) in the forums by other students. For each student, his/her reputation is the sum of the square-root of the number of votes for each post/comment that he/she has made" (Pomerantz, 2013). Top posters are the students with the highest number of reputation points.

Node Names and Coding Reference Quantity

Node Name	Sources[23]	References[24]
Affect (aggregated)	565	3103
Admiration	89	104
Belonging to this community	110	302
Competiveness	20	44
Defensiveness	27	71
Empathy	49	77
Encouragement	307	616
Frustration	58	126
Gratitude	243	510
Humor	32	76
Inspiration	52	78
Motivation	57	766
Receptiveness to critique or comment	176	256
Sympathy	35	77
Attitude	0	0
Negative	131	296
Neutral	382	1877
Positive	507	1735
Feedback	0	0
Compliment	310	623
Constructive criticism	174	310
Unconstructive criticism	20	26
Learning through P2P writing	94	105
Learning gains	382	751
Demonstrates what learned (peer review)	123	168
Evidence of incorporating feedback	50	63
Improved grades	4	5
Learned through providing feedback	257	261

[23] Sources is the number of documents that contain coding to a given node.
[24] References is the number of times an area of text was coded to that node.

Understanding	143	225
Miscommunication	3	9
Writing Elements	0	0
Additional resources	48	59
Argument and analysis	163	228
Case study	13	15
Citations	103	132
Clarity	109	139
Cohesion	42	49
Complexity and simplicity	45	50
Concision	44	51
Conclusion	51	54
Description	74	96
English language skills	37	40
Evidence and research	102	128
Factual accuracy	9	11
Figure	46	74
Format and style	107	138
Introduction	52	60
Length	28	30
Opinion	34	43
Personal experience	39	49
Plagiarism	14	24
Process to assign peer reviewers	4	4
Proofreading and grammar	50	61
Provide examples	37	51
Quotations	22	24
Structure	111	141
Title	31	35
Topic	102	136
Peer-to-peer connections (aggregated)	511	3861
Connecting outside of class	26	91
Disagreement	25	49
Feedback on Math Problem Solving	6	14
Feedback on Problem Solving	9	19
Goals or aspirations in course discipline	60	576
Introductions to peers	55	784
Offering moral or emotional Support	142	293
Offering peer review	138	341
Offering tips or help to peers	209	931
Seeking moral or emotional Support	47	86
Seeking peer review	100	133
Seeking tips or help from peers	175	393
PIT Post goal priority	0	0
1 primary goal	477	3366

2 Secondary goal	81	229
3 Ancillary goal	6	8
Post type	0	0
Course experience discussion	178	1040
Course experience question	68	161
Course material discussion	189	805
Course material question	140	319
Spam or inappropriate	9	14
Student challenges	0	0
Lack of time and energy	50	109
Less academically prepared	26	91
Less or not self-directed	39	65

Appendix B

Chemistry Writing Assignment

Objective: The objectives of this assignment are:

1) to encourage you to learn more about the chemistry related to a specific topic that interests you through research and writing.

2) to allow you to learn more about diverse topics of interest to other students by reading, responding to, and reviewing their essays.

Assignment: Pick any topic related to chemistry that interests you (some global topics are listed below to give you ideas, but you do not have to restrict yourself to that list.) Since most of the global topics are much too broad for the length limit allowed, narrow your interest until the topic is unique and can be covered (with examples) in less than a couple of pages of writing.

Once you have a topic, write an essay in which you address the following questions:

- What are the chemicals and/or chemical reactions involved with this topic?
- How does the chemistry involved with this topic relate to the material in the course?
- Are there economic or societal impacts of this chemistry? If so, then briefly describe aspects of ongoing debate, costs, etc.
- What some some questions for future research papers if you or someone else wanted to learn more about how chemistry intersects with this topic?
- Did this research lead you to formulate any new questions about the chemistry itself?

Individual Research Paper Guidelines and Requirements:

- Because other students will need to be able to read what you have written, the assignment must be submitted in English. If you are worried about grammar because English is not your native language, then please just note that right at the top of the essay and your peers will take into account the extra effort it requires to write in a foreign language.
- Think about what terms your classmates already know based upon what has been covered to date and what terms might need additional explanation.
- The final paper should be 400-600 words, not including references or

tables and figures and their captions. There is no word count police, but please use this as a guideline for length.

- Be careful not to use the "cut and paste" method for your writing. Each sentence should be written in your own words, with appropriate references to the works of others if you are getting your ideas or information for that sentence from a source.
- Online references should be used, and these should be free and available to everyone with internet access (open source, no subscription required.) At least three distinct references must be included. Wikipedia and other encyclopedias should *not* be cited, but these can be a starting point for finding primary sources. Please be sure to cite your source websites. Please provide the references at the end of the essay as a numbered list, and insert the citation at the appropriate spot in the essay body (usually right after a sentence) using square brackets around the number that corresponds to the correct reference on the list.
- The paper can include up to 3 tables/figures. Tables and figures are optional, but might be helpful in conveying your ideas and analysis. Tables and figures should include citations to sources if they are not your intellectual property (As examples, a photograph that you take would not require citation as you would hold the copyright, but a photograph that you find on the web or in the literature would require citation. A graph or table that you pull straight from a source should cite that source explicitly in the figure caption; a graph or table that you construct yourself using data from multiple sources should cite the sources of the data with an indication that you own copyright to the graph or table itself.)
- The paper should include data and/or chemistry related to the topic and might also include an analysis of the impacts of the issue upon society (yourself and the community.) Political, economic, and/or historical analysis may also be appropriate depending upon the topic. Every paper MUST contain some chemistry.
- Submission will be electronic, and submitted papers will be copied to the course forum as soon as the first peer feedback is received so that others may learn and continue the discussion. **Author names will be posted with their writing on the forum as well.** Including your name promotes accountability in your work and closer collaboration among peers.
-

Sample Writing and Sample Peer Feedback: Prof. Canelas has secured permission from a few real students from former courses to post their essays and sample peer feedback to help guide your work. These will be posted in a separate section under the "Reference Information" section on the course main page no later than the beginning of the third week of class.

Some Global Topic Suggestions: (In no particular order. Anything is fair game as long as it involves chemistry, so feel welcome to make up your own topic not related to this list. Again, please be sure to substantially narrow your topic, perhaps to a single molecule, concept, or event; these categories are much too broad but might give you some ideas of topics to explore that interest you.)

- Combustion Chemistry: Politics, Projections, and Pollution for Petroleum, Biofuels
- The Chemistry of the Senses: Taste, Odor, and/or Vision
- History, Chemistry, and Future of Antibiotics
- The Sun, Moon, Stars, and Planets: Chemistry of Astronomy
- Water, Water, Everywhere: Anything related to H2O chemistry from water medical diagnostic imaging to acid rain
- Cradle to Grave: Polymers and Plastics
- The Evolution of Chemistry for Enhanced Technology: Lighter, Stronger, Faster, Cheaper, and Cleaner
- Chemistry, Politics, and Economics of Local Pollution Issues (can be in your local area or other locations of your choice)
- Elementary, My Dear Watson: Forensic Chemistry
- The Chemistry of Diabetes, Sugar, and/or Sugar Substitutes (or pretty much any other disease, biological process, or food)
- Missing Important Food Chemicals: Scurvy, Rickets, Starvation!
- Genetic Engineering of Food (aka Messing with Molecules We Eat)
- Addictive Chemicals, both Legal and Illegal
- Chemistry of Art Preservation
- Dynamism, Diplomacy, and Disaster: Nuclear Energy, Weapons, and Waste
- Athletes on the Edge: Chemistry and Detection of Performance Enhancing Drugs in Sports
- Batteries: Portable Devices that Convert Chemical Energy to Electrical Energy
- Alternative Energy (Solar Cells, Fuel Cells)
- Chemistry of Archeology, such as Unlocking the Secrets of the Terra Cotta Warriors of Xian
- Chemistry and Controversies of Climate Change
- The Chemistry of Color
- Chemical communication: pheromones
- Poisoning: intentional or unintentional

Appendix C

Peer Feedback Guidelines for Chemistry Writing Assignment

Read your peer's essay and comment on:

1. Strengths of the paper: what aspects of the paper did you particularly enjoy or feel were well done?
2. Areas for improvements or additions to the paper, ideally with specific suggestions.
3. Insights you learned from reading the paper or what you found to be the most interesting aspects of the topic.

Please give feedback in paragraph form rather than as single sentences underneath the guidelines. Please remember: we are not grading these essays with a score. Instead, we are learning about chemistry from each other through the *processes* of researching, writing, reading, and providing comments for discussion.

Appendix D

I am a Writer Assignment from English Composition

Write a brief essay (~300 words) in which you introduce yourself as a writer to your classmates and instructor. How would you describe yourself as a writer? What are some of your most memorable experiences with writing? Please draw on your experiences with writing and refer directly to some of these as you introduce yourself as a writer. After you have written and posted your essay, please read and respond to two or three of your classmates' postings.

Appendix E

Four Major Writing Projects, English Composition

Project One: Critical Review
The Uses and Limits of Daniel Coyle's "The Sweet Spot."

In this project, I will ask you to write a 600-800 word critical review of Coyle's article, summarizing the project in his terms, quoting and analyzing key words and passages from the text, and assessing the limits and uses of his argument and approach.

Project Two: Analyzing a Visual Image
In your second project, I will ask you to develop a 600-800 word analysis of a visual representation of your chosen field of expertise. I will ask you to apply Coyle's and Colvin's ideas, and the forum conversations by classmates, to examine how expertise in your chosen area is represented and how it reflects, modifies, and/or challenges ideas about expertise: How is expertise represented visually? What does the image suggest about what it takes to be an expert in this field? How is expertise being defined in this image?

Project Three: Case Study

In this project, I will ask you to extend your work with Projects One and Two by researching additional scholarship about expertise in your chosen area, reading more texts about expertise theory through a crowd-sourced annotated bibliography (a collection of resources, with summaries, posted by all students), and applying those to a particular case study (example) of an expert or expertise in your field. I will ask you to extend these scholarly conversations through a 1000-1250 word case study in which you can articulate a position about expertise or an expert in the area of inquiry you have chosen.

Project Four: Op-Ed

Since the academic ideas are often made public (and arguably should be), I will ask you to write a two-page Op-Ed about a meaningful aspect of your chosen area of expertise: What aspects are important for others to consider? What advice would you have for people desiring to become an expert in this area? What are the politics and cultures involved with establishing and defining expertise in this particular area?

Sample Full Project Assignment, English Composition, Project 3, Case Study

Project Components and Key dates

Project 3 will be completed in sequenced stages so you can move through the writing process and have adequate time to draft and revise by integrating reader feedback.

- Contribute to our annotated bibliography on the discussion forums: (Weeks 6-8)
- First draft due, with "note to readers": May 13, 9:00 am EDT (-0400 GMT)
- Respond to Peers (formative feedback): May 20, 9:00 am EDT (-0400 GMT)

Note: You MUST get your comments back to the writers on time so they can meet the next deadline!

- Reflect on Responding to Peers
- Revise and Edit: Feedback available beginning May 20, 10:00 am EDT (-0400 GMT)
- Final draft due, with reflection: May 27, 9:00 am EDT (-0400 GMT)
- Evaluate and respond to Peers (evaluative feedback): June 3, 9:00 am EDT (-0400 GMT)
- Reflect on Project 3

Purpose: Learn how to research an in-depth example of expertise.

Overview

Case studies offer academic writers the chance to research a particular example in a deep, sustained way, and then consider the ways in which that case study might offer generalizable conclusions. For Project 3, extend your work with Projects One and Two by researching additional scholarship about expertise in your chosen area, read more texts about expertise theory through a crowd-sourced annotated bibliography (a collection of resources, with summaries, posted by all students), and apply that research to a particular case study (example) of an expert or expertise in your field. Specifically, we will continue to work with the elements we learned in Units 1 and 2, as well as build on them by focusing on how to:

- conduct research;
- write an extended argument;
- develop an intertextual conversation;
- understand different limits of and uses for popular sources and scholarly sources;
- create effective introductions; and
- write strong conclusions.

Assignment

For this third writing project, I am asking you to build on your work in Project 1 and Project 2, and extend our conversations about expertise through a 1000-1250 word case study in which you articulate a position about expertise or an expert in the area of inquiry you have chosen. Your case study can be about a particular person or aspect of expertise in your chosen area. Use this case study to generate an argument about expertise. See below for ideas about the questions you might use to develop your argument.

Here are a few examples of possible case studies, along with potential resources:

a. Area of Expertise: Software Engineering.

Potential Case Study: Leading Expert in Software Engineering

Potential Sources: biographical information about that expert; information about the institution in which he or she works; information about the elements of softwareengineering he or she has mastered or developed.

b. Area of Expertise: Cooking

Potential Case Study: Michelin Ratings

Potential Sources: information about the history of Michelin Ratings; information about the current restaurants named in the ratings; disagreements around Michelin; information about rating systems that compete with Michelin.

c. Area of Expertise: American Civil War

Potential Case Study: Reenactment Groups

Potential Sources: descriptions of various reenactment groups; history of these groups; structure, activities, and schedules for these groups.

For sample case studies, please visit our course's Readings & Resources page. You will find that case studies appear in a variety of formats. You can choose the format that you believe fits best for your case study.

Your steps for this project include the following:

- Identify a potential case study you would like to use for Project 3. Remember that the process of research is sometimes recursive, and you might find through your research that you would like to change or modify your original idea for a case study. This is a natural part of the research process.
- Find and read texts about this case study.

- Visit the Discussion Forum, Annotated Bibliography and contribute annotated entries; read through your classmates' contributions to see other potentially useful research. (See Annotated Bibliography Instructions for more specifics on this.) Using this research, draft and revise your Project 3 essay within the appropriate deadlines for drafts, peer feedback, and revision.

Readers

Your readers will be interested in questions about expertise, but are perhaps unfamiliar with the texts you have read or the area of expertise you have chosen.

Questions to Help You

Consider the following questions as you develop your argument:

- What can we learn about expertise by researching a particular case study?
- What does it take to succeed based on this case study?
- What are the defining features of expertise based on this case study?
- What can you learn about expertise based on this case study?
- Based on this case study, how is expertise being defined?
- How might this case study reinforce, challenge, or otherwise modify our prior thinking about expertise, such as the ideas of Coyle, Colvin, or others?
- How might this case study raise new questions about expertise?
- What questions does the case study raise for you?

Integrating Evidence and Citing the Evidence

Integrate evidence into your essay by including quotes and/or paraphrases from the research.

Strategies for effectively incorporating quotes and paraphrases are described in the video,

"Integrating Evidence." Refer to OWL for specifics on the school of citation you are choosing to write within. You should choose a school of citation with which you would like to gain more familiarity and/or that seems most relevant for your future pursuits. Include a "Works Cited" or

"References" page at the end of your work listing all texts you have referred to.

Submission Guidelines

Post all documents to the appropriate Assignments section no later than the due date so your responders can read and send you comments for your final version.

Grading Criteria

An excellent project will meet the following criteria, showing that you can:

- present the case study thoroughly
- conduct research and evaluate sources
- effectively use the case study to support and/or develop your own argument
- effectively integrate evidence in the form of details about the case study, as well as quotes and paraphrases from sources
- employ scholarly conventions for citing sources, including in-text citations and works-cited page
- organize the essay clearly
- develop paragraphs that achieve paragraph unity
- create effective introductions and conclusions
- revise deeply as well as edit carefully
- include an effective title

Appendix F

Sample Formative and Evaluative Peer Feedback Rubrics, Project 3

Peer Response, Project 3, Draft 1: Case Study on Expertise (Formative Feedback)

****Reading and Responding to Other Writers Makes You a Better Writer

and Will Also Improve Your Own Project Draft****

Peer feedback is crucial to our work as writers: it helps the writer improve his or her draft and grow as a writer, but it also helps you, as a responder, improve your draft and advance more generally as a writer. I am asking you to respond to three people's drafts. For this first draft, provide formative feedback--that is, feedback that will help a writer improve and revise his or her draft. To do so, first review the goals of the assignment and our course's overall learning objectives, and then provide responses to the nine feedback questions below. Responding by the specified due date is crucial so that the writer can submit his or her next draft on time. Your classmates are depending on you!

...

<u>Providing Formative Feedback For Project 2, Draft 1</u>

Using the writer's "Note to Readers: My Queries," as well as our learning objectives/criteria for this unit and the overall course (see above), answer each of the following questions so you can provide feedback to your colleague in order to help him or her improve this draft and grow as a writer:

1. Respond to the writer's "Note to Readers: My Queries"

2. Where does the writer offer details about the case study? Is this sufficient to convey the important aspects of the case study to readers who may not be familiar with this?

3. Where does the writer go beyond description to pose a question about expertise or to show how the case study reflects, contrasts, or modifies ideas about expertise?

4. Summarize in a sentence or two what the writer is arguing, if you can. If you cannot, say what the writer might do to make the argument more clear.

5. What evidence does the writer draw on to support and/or develop his or her argument? Has the writer effectively integrated, discussed, and cited research? If not, say what the writer might do to integrate and cite research more effectively.

6. Are there so many unconventional features in the writing (spelling, sentence structure, vocabulary, and so on) that you found them interfering with your reading? Identify in particular one of these features so the writer can focus on it for his or her revision.

7. Did you find the introduction effective? If so, please describe what features make them effective. If not, make a few suggestions for how the writer can improve it.

8. Did you find the conclusion effective? If so, please describe what features make them effective. If not, make a few suggestions for how the writer can improve it.

9. What did you like best about this essay?

10. What did you learn about your own writing/your own project based on responding to this writer's project?

Peer Response, Project 3, Final Version: Case Study on Expertise (Evaluative Feedback)

****Reading and Responding to Other Writers Makes You a Better Writer

and Will Also Improve Your Own Project Draft****

Evaluative feedback enables writers to reflect on not only the writing project, but also

themselves as writers. Providing effective evaluative feedback will enable your colleagues to move forward to Project 4 and advance as writers. Providing evaluative feedback will enable you to grow as a writer as you reflect on what another writer's project can teach you about writing.

…

Providing Evaluative Feedback For Project 3, Final Version

Using the grading criteria above, the writer's "Note to Readers," and our overall learning

objectives/criteria for this unit, you will be scoring your colleague's projects on a 6-point scale in order to help them improve as writers for subsequent writing occasions.

Think of the 6-point scale as two halves:

a top half of 4, 5, or 6 representing different levels of successful projects and

a lower half of 1, 2, and 3 representing different levels of unsuccessful projects.

You can think of a paper scoring 5 as the center of success and one scoring 2 as the center score for lack of success, with the other scores as a minus or plus. Thus a score of

4 is successful, but marginally so, a kind of 5-. A score of 6 is exceptionally successful, a kind of 5+. Only one whole number, without pluses or minuses, can be entered on the SCORE line. Your score will be combined with three other peer scores to obtain a grade for the writer's project.

Score of 6: This project will meet all criteria and goals for unit 3 and be very clear and well written. It need not be perfect but it will be well reasoned, show a deep understanding of the case study, evaluates and discusses relevant research, and shows a compelling discussion of how the case study reflects, contrasts, or modifies our thinking about expertise. The project uses the case study to raise new questions about expertise. The introduction and conclusion are strong. Evidence is integrated effectively, and the title is strong. Citations are mostly correct.

Short description: Exceptionally successful

Score of 5: This project not only presents the case study, but also uses it to make an argument about expertise. It is clear and well written. The project includes relevant research. Paragraphs are unified and the paper is organized clearly. The introduction and conclusion are strong. Evidence is integrated effectively, and the title is strong. Citations are mostly correct.

Short description: Successful

Score of 4: This project describes the case study in an organized way, but it does not offer a thorough understanding of it, and has little or nothing to say about its relation to the issue of expertise. It may have a few unconventional features of written English, such as vocabulary, sentence construction, etc., but these do not for the most part interfere with the communication of the writer's ideas. It is for the most part clearly written. Paragraphs are mostly organized clearly and unified. Research may be a bit limited, and evidence is integrated effectively some of the time. Distinctions are rarely made among the sources and quotations are sometimes inserted without being discussed. The introduction and/or conclusion are somewhat effective. Citations

are present and mostly correct. The title is somewhat effective.

Short description: Successful, but marginally so

Score of 3: This project shows only a superficial understanding of the case study and limited description of it. It may have some unconventional features of written English, such as vocabulary, sentence construction, etc., that interfere with the communication of the writer's ideas. It offers little by way of argument. The project uses little research and does not evaluate or discuss the sources. Evidence is only occasionally integrated effectively, and/or not much evidence is used. Citations are often incorrect. The introduction and /or conclusion are present, but not effective. The title is largely ineffective.

Short description: Unsuccessful, but marginally so

Score of 2: This project pays little attention to the case study or shows little understanding of it. It offers very little by way of argument, and hardly any research. It may also contain some unconventional features of written English, such as vocabulary, sentence construction, or other features that interfere with the communication of the writer's ideas. The essay is not organized clearly, and the paragraphs often are not unified. Evidence is for the most part not integrated effectively, and/or very little evidence is used. Citations are mostly incorrect or absent. The introduction and /or conclusion are not effective. The title is ineffective.

Short description: Unsuccessful

Score of 1: This project has misunderstood the nature of the assignment or the meaning of the case study and presents many unconventional features of written English, such as vocabulary, sentence construction, or other features that interfere with the communication of the writer's ideas. Evidence is not integrated effectively, and/or no evidence is used. The paper is disorganized and paragraphs are not unified. Citations are incorrect or absent. The title is absent or ineffective.

Short description: Extremely Unsuccessful

Fill in the following boxes:

What overall comments do you have for the writer as he or she moves on to Project 4?

What did you learn about you your own writing based on reading and evaluating this writer's project?

Appendix G

Final Reflective Essay Assignment, English Composition

Reflection is crucial to growing as a writer. Reflection helps you consider how you can apply what you have learned from one experience to subsequent writing and non-writing occasions. Now that you have nearly finished this course, please reflect on what you have learned about yourself as writer. This quiz is credit/no credit: if you complete it, you get credit; if you do not complete it, there will be no credit. Part of the quiz asks you to cut and paste text from your course writing, so please have the following available as you complete the Reflection: Drafts and Final Versions of Projects 1-4, Feedback to and from Colleagues, Forum Comments, and Reflective Quizzes. The quiz is due June 12, 9:00 a.m. GMT -0400. You may not apply late days.

The following are our course learning objectives:

- ☐ Summarize, analyze, question, and evaluate written and visual texts
- ☐ Argue and support a position
- ☐ Recognize audience and disciplinary expectations
- ☐ Identify and use the stages of the writing process
- ☐ Identify characteristics of effective sentence and paragraph-level prose
- ☐ Apply proper citation practices

Discuss how to transfer and apply your writing knowledge to other writing occasions Imagine that you have compiled a portfolio of all your work from this course (Drafts and Final Versions of Projects 1-4, Feedback to and from Colleagues, Forum Comments, and Reflective Quizzes) and you are preparing to share it with others. These potential readers might be administrators at a school you are applying to, current or potential employers, friends, or other acquaintances. Your task is to write a cover letter that introduces your work and makes an argument about your understanding and achievement of the course learning objectives.

In the space provided here, discuss what you have learned in this course and choose 2-4 of our course learning objectives, describing each objective and referring specifically to particular passages from your coursework that demonstrate your progress towards and/or struggles with that objective. Indicate why you have chosen those objectives as the most important for you. Cut and paste specific portions of your coursework, and use them as evidence for your argument. In this way, by having an introduction, argument, evidence, and conclusion, your “portfolio cover letter” will both discuss and demonstrate how effectively you have achieved the goals of the course. When referring to your work, indicate clearly the piece of writing (i.e., Project 3) and page number(s) for your readers' ease of reference.

Length: ~500-750 words

IRRODL
THE INTERNATIONAL REVIEW OF RESEARCH IN OPEN AND DISTANCE LEARNING

Evaluating the Validity and Applicability of Automated Essay Scoring in Two Massive Open Online Courses




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Abstract

The use of massive open online courses (MOOCs) to expand students' access to higher education has raised questions regarding the extent to which this course model can provide and assess authentic, higher level student learning. In response to this need, MOOC platforms have begun utilizing automated essay scoring (AES) systems that allow students to engage in critical writing and free-response activities. However, there is a lack of research investigating the validity of such systems in MOOCs. This research examined the effectiveness of an AES tool to score writing assignments in two MOOCs. Results indicated that some significant differences existed between Instructor grading, AES-Holistic scores, and AES-Rubric Total scores within two MOOC courses. However, use of the AES system may still be useful given instructors' assessment needs and intent. Findings from this research have implications for instructional technology administrators, educational designers, and instructors implementing AES learning activities in MOOC courses.

Keywords: Massive open online courses; assessment; automated essay scoring systems

Introduction

A massive open online course (MOOC) provides online course content delivered by professors from top universities to any individual who chooses to enroll in the course. The subject of MOOCs is currently one of the most hotly debated topics in higher education. Proponents suggest that MOOCs could render traditional brick-and-mortar universities obsolete, while opponents maintain that high attrition rates and limited quality measures make MOOCs a threat to effective learning (Watters, 2013). As MOOCs have become more widespread, with some institutions offering badges or accepting MOOCs for credit, assessment has moved to the front and center of the conversation (Sandeen, 2013). A major question remains: Can MOOCs provide and adequately assess authentic, higher level student learning experiences?

Currently most assessment in MOOCs is based on computer-scored multiple choice questions, formulaic problems with correct answers, logical proofs, computer code, and matching items, often with targeted feedback based on the responses given (Balfour, 2013). While this type of assessment works well in certain disciplines, others rely more on open-ended writing assessments for students to fully demonstrate their learning. Many MOOC environments provide tools for delivering open-ended writing assignments and either self- or peer-scoring with a rubric, but the quality of the scoring and feedback can vary greatly, possibly making it inappropriate for high-stakes assessment. Consequently, there is a need for valid and reliable automated scoring of open-ended written assessments in MOOCs.

Open-Ended Assessment in Online Learning

Open-ended assessments are commonly used to measure students' writing skills, conceptual understanding, and higher order thinking skills such as evaluating, analyzing, and problem solving. By forcing students to construct a response rather than choose from a list of possible answers, students are more fully able to demonstrate what they know and are able to do. Several studies have highlighted the importance of open-ended writing assignments in facilitating higher level thinking, allowing students to make connections and think clearly and critically about important issues (Kellogg & Raulerson, 2007). A study of multiple choice versus essay writing assessments of second year college students found that essay prompts were associated with deeper level learning approaches, while multiple choice formats were more often associated with surface-level learning (Scouller, 1998). Open-ended assessments provide students with more opportunities to apply their knowledge and skills to authentic contexts and to transfer knowledge, while timely scoring provides feedback to students that leads to increased achievement (Chung, Shel, & Kaiser, 2006; Vonderwell et al., 2007; Wolsey, 2008; Gikandi, Morrow, & Davis, 2011; Crisp & Ward, 2008). For these reasons, open-ended assessment items enable students to demonstrate their higher level learning in a much richer fashion than other types of machine-scored items.

The use of open-ended responses in online course environments has become standard practice. Peers, teaching assistants, or instructors often use electronic rubrics to score open-ended responses and provide feedback to students. Timely feedback is particularly important in an online environment because it can (1) help break down barriers that exist for students seeking clarification of information (Wolsey, 2008); (2) enable students to quickly revise misunderstandings; (3) encourage sustained student engagement (Tallent-Runnels et al., 2006); and (4) promote student satisfaction (Gikandi et al., 2011). While the tools exist to gather open-ended assessment data from students in online environments, the scoring and feedback mechanism has proven problematic when scaling to large numbers of students.

Open-Ended Automated Assessment in MOOCs

Incorporating open-ended assessments with valid and reliable scoring has the potential to transform the MOOC experience, especially in the liberal arts disciplines. Several MOOC platforms have begun utilizing assessment tools that allow students to engage in critical writing and free-response activities. However, the large student populations make it impossible for course instructors to score all open response items. Peer assessment functionality exists, but ways of holding reviewers accountable for quality scoring and feedback often do not. In addition, recent studies have emphasized the importance of automatic feedback for asynchronous distance learners who cannot wait for instructor-specific feedback (Farrús & Costa-jussà, 2013). For these reasons the MOOC platform, edX, is experimenting with an automated essay scoring (AES) system that can quickly score student written responses.

The New York Times announcement of the innovative nature of the edX AES scoring tool generated discussion on several educational blogs (for example, Mayfield, 2013; Tan, 2013) and in the higher education press (for example, Markoff, 2013). The edX AES system uses an innovative machine learning algorithm to model the characteristics of responses at different score points using an instructor-developed rubric and approximately 100 instructor-scored student responses, which is a smaller number of required instructor-graded calibration essays than many other AES systems (Dikli, 2006). While AES systems have been around for several years, there are mixed results about their effectiveness.

The first AES system, known as the Project Essay Grader (PEG), was developed in 1966 as a potential grading strategy to help relieve teachers of the burden of grading essays for large classes. While this system was accurate at predicting human scores and had a fairly simple scoring method, critics of this early system argued that it measured only surface-level features of writing and could be deceived by students into giving higher scores to longer essays (Dikli, 2006). The *e-rater* system used by the Educational Testing Service (ETS) has been the subject of many AES-related articles and is generally found to be consistently predictive of scores given by human graders (Burstein & Chodorow, 1999). However, studies conducted by Wang and Brown on the *e-rater* resulted in significant differences between machine graders and human graders (2007) and a lack of significant correlations among machine and human graders (2008), giving academics cause for concern. In 2012, AES critic Les Perelman submitted an essay to the ETS *e-rater* system composed of real words written in a nonsensical and incoherent way, and received the highest possible score for it (Gregory, 2013).

While still in the developmental phases, almost no research has been conducted on the validity, perceptions, and instructor best-practices of the edX AES system. Although the tool was successfully piloted in a chemistry course where 80% of students believed their score was accurate (J. Akana, personal communication, August 21, 2013), additional research is needed to calibrate and determine the reliability of the scores produced in different contexts and with different types of learners. An additional area for research is the differential use of holistic versus trait/rubric grading through AES systems. Holistic scoring involves giving one score based on an overall assessment of an assignment, while rubric (also referred to as analytic) grading refers to assigning multiple scores based on several features of an assignment; for example, analytic components of an essay might be clarity, organization, grammar, and spelling (Burstein, Leacock, & Swartz, 2001). The edX system utilizes both methods, creating both rubric-level and holistic scores for student essays, but records the holistic score as the final essay grade.

Overall, there is a growing call for research investigating the capabilities of AES tools, how faculty and students view and utilize them, and how they might be best embedded in MOOCs to promote greater critical thinking and interaction with course content, and to be used for high-stakes assessment. To address this concern, data was collected from the first two MOOCs to utilize the edX AES system. In this study, we investigated the following research questions: To what extent is the current edX machine-graded assessment system (both holistic and rubric-total) valid, reliable and comparable to instructor grading? Additionally, do the AES-graded assignments (AES-Holistic and AES-Rubric total) correlate with non-essay assignment grades in the course?

Study One

Method

Study One included MOOC student samples from an edX Pharmacy course in fall 2013, with an enrollment of approximately 15,000 students. The current study utilized a causal-comparative design, a non-experimental research design which involves data collection and analyses that allow for group comparisons upon a particular variable of interest (Martella, Nelson, & Marchand-Martella, 1999). In this study, the researchers examined data from three groups; specifically, comparisons were made between the AES-Holistic graded score group, the AES-Rubric graded score group, and the instructor-graded score group. Additionally, correlational analyses were used to investigate potential relationships among AES- and instructor-scores and patterns of grading. Both causal-comparative and correlational designs have been used in prior AES studies to compare AES and human-grading as well, and were incorporated to more fully explore relationships among both mean differences and grading patterns (Wang & Brown, 2007; Wang & Brown, 2008).

The essay assignment involved students reflecting on patient compliance with medication prescriptions, and asked students to write a short-answer response of about 5 to 7 sentences. The instructor then graded 100 essays to calibrate the AES system. The rubric for the assignment consisted of 4 different general sections (Understanding, Support, Organization, and Content), on a scale of 0 -2, with total scores ranging from 0 to 8. Approximately 1,090 students completed this assignment, and 206 of the AES-scored essays were randomly selected, de-identified and re-graded by the instructor who originally calibrated the AES system, using the same rubric used for AES calibration.

Results

Prior to analyses, we statistically and visually inspected the score distributions for the three rating systems to assess their normality. We determined that the scores were substantially deviant from a normal distribution, which was indicated by excessive levels of skewness (AES-Holistic = -1.35, AES-Rubric = -1.98, Instructor = -2.12) and kurtosis (AES-Holistic = 1.89, AES-Rubric = 3.78, Instructor = 4.59) and inspection of frequency distributions, boxplots, and Q-Q plots. The non-normality of the score distributions was likely due to the eight-point scale used in calculating total essay scores. Therefore, all analyses used were non-parametric. Multiple analyses were conducted in order to determine the nature of the relationship between the two AES scoring systems (AES-Holistic and AES-Rubric Total) and the instructor's grading.

Wilcoxon signed rank tests (non-parametric repeated measures t-tests) were used to compare the average scores of each of the three essay scorers. Results indicated that there was a significant difference between the Instructor's and AES-Holistic's grading ($S = -5731$, $p < .0001$), such that the instructor gave students an average of 1.27 more points on the essay than the AES-Holistic grader. However, the AES-Rubric Total and Instructor scores did not significantly differ ($S = 479.5$, $p < .054$), with the instructor on average scoring essays .24 points higher than AES-Rubric Total. The averages of the two AES grading systems were also compared. The AES-Rubric Total was an average of 1.02 points greater than the AES-Holistic Score, which was a significant difference ($S = 5404$, $p < .0001$).

Spearman correlations found that there were significant relationships between all three essay grades. The highest correlation was between the AES-Holistic and AES-Rubric Total ($r_s = .70$, $p < .01$), with moderate correlations between each of these with the Instructor score ($r_s = .59$ and .57, respectively, $p < .0001$). Ordinal logistic regressions were used to predict expected Instructor total based on the AES scores. AES-Holistic scores significantly predicted instructor scores, $B = .65$ ($e^{0.65} = 1.91$, $p < .0001$), indicating that for every point given by the AES-Holistic scorer, the odds of a one-point gain in the Instructor score increases by a factor of 1.91. Correspondingly, there is a .65 probability that the instructor will give a point for each point that the AES-Holistic scorer assigns. The AES-Rubric Total was also found to be a significant positive predictor of Instructor score, $B = .59$ ($e^{.59} = 1.81$, $p < .0001$), meaning that as the AES-Rubric Total increases one point, the odds of a one-point gain in Instructor score increases by a factor of 1.81.This results in there being a .64 probability that the instructor will give a point for each point that the AES-Rubric scorer gives.

Percent agreement between the AES and Instructor grades were calculated. The agreement between individual rubric scores assigned by the Instructor and AES were high, ranging from 73.89% to 79.31% (see Table 1). Agreement between AES-Rubric Total and Instructor-total was lower though still relatively high, 55.17%. The percentage agreement was lowest between the AES-Holistic and Instructor grade, 17.24%.

Table 1

Percent Agreement between Instructor and AES-Scores – Pharmacy Course

	Rubric 1	Rubric 2	Rubric 3	Rubric 4	Rubric total	Holistic score
Percent agreement	79.31	77.83	75.37	73.89	55.17	17.24

Weighted kappas were also calculated to test whether there were significant differences between adjacent agreement scores. The AES-Holistic and Instructor Total weighted kappa coefficient was significantly different ($\kappa = .22$, $Z = 6.85$, $p < .0001$), indicating that there are significant differences in the grading of the AES-Holistic and Instructor. Similar findings were found for the AES-Rubric Total and Instructor Total agreement ($\kappa = .37$, $Z = 7.86$, $p < .0001$).

Lastly, Spearman correlations were conducted to determine the association between the three AES-essay grading systems and other course grades. These grades included the average of all homework assignments not including the essay grade, and the average of lab assignments, which were short quizzes following lecture videos and reading passages. All correlations were moderately low. The average lab grade had the highest associations with essay grades, having equal correlations with the AES grades ($r_s = .25$, $p < .00001$) and being the least associated with the Instructor Total ($r_s = .14$, $p < .05$). The correlations between average homework grade excluding the essay grade was most highly correlated with AES-Rubric Total ($r_s = .24$, $p < .0001$), followed by the AES-Holistic ($r_s = .22$, $p < .0001$), and the least with the Instructor Total ($r_s = .19$, $p < .01$).

Discussion

Past research suggests that, although the demand for AES systems is increasing, there is no consensus on the ability of these systems to automatically grade student essays and consistently predict instructor/human grading (Dikli, 2006). Most generally, the results of this study extend previous research by investigating the use of AES-Holistic and AES-Rubric systems in MOOCs, and how comparable they are to one another, instructor grading, and non-essay course grades (Deane, Williams, Weng, & Trapani, 2013; Rich, Harrington, Kim, & West, 2008; Shermis, Koch, Page, Keith, & Harrington, 2002). For this course, percent agreement between individual rubric scores assigned by the Instructor and AES-Rubric scorer were high, suggesting that inter-rater reliability on specific rubric criteria was moderately high for the AES-Rubric grader, though not for the AES-Holistic grader. Though high adjacent-agreement statistics are often easier to achieve than exact-agreement (see Cizek & Page, 2003), these results are promising for the use of the AES-Rubric grader.

Additional findings also emphasize the difference between holistic and rubric-total AES grading. Results indicated that the AES-Holistic Total and AES-Rubric Total were most highly correlated, which is consistent with research suggesting that trait ratings and holistic ratings are often correlated (Lee, Gentile, & Kantor, 2008; Deane, Williams, Weng, & Trapani, 2013) and can be as good or better than the correlation of ratings between two human raters (Shermis et al., 2002). Our data further suggest that for Study One, both AES systems tended to give lower scores than the instructor, and that these differences were most dramatic between the Instructor and AES-Holistic score. Consequently, these results indicate that the AES and instructor's scores are significantly related, but that the instructor assigned significantly higher grades than either AES-scoring system. This parallels past studies that have found instructors to grade higher than AES systems due to a more nuanced grasp of content, metaphor, and other rhetorical devices (Byrne, Tang, Tranduc, & Tang, 2010). However, the AES-Rubric Total and Instructor scores did not significantly differ, further suggesting that this particular AES system might be most comparable to Instructor grading when utilizing an AES-Rubric total score, as opposed to an AES-Holistic score.

It is also important to note that, although automatically-scored essay grades and other indicators of course success were moderately correlated, course grades appeared to be the least correlated with the instructor's essay grading. This may be due to the tendency of the instructor-total grades to be higher than the other AES grades and a subsequent ceiling effect, which could lead to lower course-essay grade correlations. In other words, little variability exists at extreme ends of a scoring scale when there is not a sufficient range of scores provided, and in this case it is possible that the instructor unintentionally created a maximizing effect by assigning higher essay grades (Keeley, English, Irons, & Henslee, 2013). Additionally, critics of AES systems have argued that they are unable to accurately score higher level writing tasks that would reflect authentic college-level learning and ability (Condon, 2013; McCurry, 2010). Consequently, these findings suggest a need to investigate the pedagogical differences between these different assessment types in MOOCs, and how they might differentially measure learning objectives within MOOC education.

Study Two

Method

Study Two sought to replicate the findings from Study One using an assignment with a more elaborate rubric and generally longer essay responses. Similar to Study One, this study also utilized a combined causal-comparative and correlational study design to investigate both mean differences and relationships among AES-Holistic graded scoring, the AES-Rubric scoring, and instructor scoring of student essays. Participants included MOOC students from a fall 2013 philosophy course with approximately 29,000 students enrolled. The essay assignment asked students to reflect on a historical event and apply course-concepts to their analysis, with no word limit for responses. The rubric for the assignment consisted of 7 different general sections (Intelligibility, Clarity, Understanding, Support, Depth, Interpretation, and Comparison), on a scale of 0 -3, with total scores ranging from 0 to 21. Students first self-assessed their written work using the rubric, and then submitted their assignments for AES-grading. Approximately 423 students completed this assignment, and 128 of the AES-scored student surveys were randomly selected, de-identified and re-graded by the instructor who originally calibrated the AES system, using the same rubric used for AES calibration.

Results

Prior to analyses, we statistically and visually inspected the score distributions for the three rating systems to assess their normality. The distributions had levels of skewness (AES-Holistic = -0.77, AES-Rubric = -0.76, Instructor = -0.54) and kurtosis (AES-Holistic = 0.83, AES-Rubric = 0.69, Instructor = -0.51) within the appropriate ranges to be considered normally distributed. Based on this finding and a visual analysis of histograms, boxplots, and Q-Q plots, we determined that the scores were approximately normally distributed and that parametric statistical procedures were appropriate for the series of analyses. Paired samples t-tests were conducted to determine whether there were differences between the mean AES essay grades and Instructor Total. The average difference between the AES-Holistic score and Instructor total was .36, and not statistically significantly different (t = 0.88, p = .38). However, the AES-Rubric Total was significantly different than the Instructor Total (t = 2.43, $p < .05$), with the AES-Rubric Total being an average of 1.02 points higher than the Instructor Total. The AES-Holistic and AES-Rubric Total essay scores were also significantly different (t = 3.73, $p < .001$), with the AES-Rubric Total being an average of .66 points higher than the AES-Holistic Total.

Pearson correlations were conducted to investigate the associations between the three essay grading systems. The AES-Rubric Total and AES-Holistic had the highest correlation, r = .88 (p < .001). The Instructor Total had almost identical correlations with the AES-Holistic (r = .62, p < .0001) and the AES-Rubric Total (r = .60, p < .0001). Linear regressions analyses revealed that the AES-Holistic score was a significant predictor of Instructor Total (B = 0.92, t(1) = 8.79, p < .0001). This shows that for every one point given by the AES-Holistic, the Instructor Total is expected to increase by .92 points. The AES-Rubric Total was also a significant predictor of Instructor Total (B = 0.85, t(1) = 8.45, p < .0001), with every point increase on the AES-Rubric Total reflecting a .85 point increase in the instructor given essay score.

Percent agreement between the AES and Instructor rubric scores and essay grades were calculated. The agreement between individual rubric scores given by the Instructor and the AES system ranged from 35.94% to 50.00%. The Instructor Total had 14.06% agreement with the AES-Rubric Total and 13.28% agreement with the AES-Holistic score (see Table 2). To look further into the agreement between AES and Instructor scores, weighted kappas were calculated. The AES-Holistic and Instructor Total weighted kappa was significant (κ = .37, Z = 7.93, p < .0001), indicating that they differed in terms of weighted-score agreement. Analyses indicated that the essay grading by the AES-Rubric Total and the instructor also significantly differed (κ = .40, Z = 8.35, p < .0001).

Table 2

Percent Agreement between Instructor and AES-Scores – Philosophy Course

	Rubric 1	Rubric 2	Rubric 3	Rubric 4	Rubric 5	Rubric 6	Rubric 7	Rubric total	Holistic score
Percent agreement	46.88	49.22	46.09	35.94	50.00	40.63	42.97	14.06	13.28

Pearson correlations were calculated to analyze the relationship between the essay grades and another significant student-assessment. As a measure of non-essay student achievement, analyses utilized the “Lecture Sequence” average, which was the average of quizzes given after each video lecture. Correlations between AES-Holistic essay-scores and the Lecture Sequence average were small and non-significant (r = .11, p = .07). The AES-Rubric Total was also not significantly related to Lecture Sequence average (r = .10, p = .10). Instructor Total was not significantly related to the Lecture Sequence average, with a correlation of r = -.04 (p = .69).

Discussion

These analyses reveal that the AES grading systems were significantly correlated with Instructor Totals, though the instructor tended to assign slightly lower essay grades than both AES graders. Additionally, there was no significant difference between the Instructor and AES-Holistic scores, and all three grading systems (Instructor, AES-Holistic, and AES-Rubric) were positively, highly, and significantly correlated. This aligns with previous research suggesting that AES systems are often highly correlated (Johnson, 1996; Kakkonen, Myller, Sutinen & Timonon, 2008; Shermis et al., 2002).

Our findings suggest that, although asignificant mean difference existed between Instructor and AI-Rubric scores, there was actually high convergent validity among the three grading systems. This result is comparable to past studies indicating that well-developed AES systems can often produce grades comparable to skilled human graders (e.g., Shermis, Burstein, Higgins, & Zechner, 2010). For example, a study on an ETS research initiative called "Cognitively-Based Assessments of, for, and as Learning" (CBAL) by Deane and colleagues (2013) noted that perhaps rubric and holistic grading is best used when dividing up the grading tasks appropriately by grader. For example, the aspects of writing assessment that most closely match between the AES system and human graders (such as basic structure, grammar, and spelling) can be left to computers, while the more intricate aspects of writing quality, argumentation, and effective analysis can be reserved for human grading. Additionally, AES-essay grades and non-essay assignment grades were not correlated, corresponding with research highlighting the idea that different assignment types may measure different constructs in student learning or course outcomes (Scouller, 1998).

Though these analyses were encouraging regarding system validity, percent agreement analyses suggested that there is a significant discrepancy in the pattern of grading by both the AES systems and instructors. Specifically, inter-rater reliability analyses suggested that, on specific rubric criteria, the AES-Rubric total and Instructor scores were quite low. Findings such as these highlight the importance of using multiple metrics of validity and reliability when examining AES systems (Yang et al., 2001; Dikli, 2006). In other words, as AES tools continue to evolve and improve, it may be necessary to support these tools with supplemental measures of writing proficiency and ability, particularly in regards to the learning objectives being assessed within the writing task.

Another possible reason for the discrepancy in grading pattern may be attributed to the essay length, which has been shown to be highly correlated with both holistic and rubric scoring (Lee, Gentile, & Kantor, 2008). For example, Lee and colleagues' (2008) study on the relationship between individual rubric criteria scores and holistic scoring suggest that statistically controlling for essay length may aid in the usefulness and interpretability of rubric scores in AES systems. Along with other researchers of AES tools (Lee, Gentile, & Kantor, 2008; Shermis et al., 2002), we suggest that exploring the relationship between essay length, human grading, and AES scoring (both holistic and rubric) would be useful for future applications of automatic grading systems.

Conclusion

A series of different quantitative analyses was chosen to address the research questions, using the appropriate statistical analyses to obtain information on mean differences, correlational informational, and percent agreement examinations of different graders (AES-Holistic, AES-Rubric, and Instructor). Due to the amount of data and the subjective nature of essay grading that is a point of contention between proponents and critics of AES systems (Wang & Brown, 2007; Valenti, Neri, & Cucchiarelli, 2003), this methodology and various analyses methods was considered appropriate for both studies.

Overall, as the two study assignments had different rubrics and content, it is not reasonable to directly compare Study One and Study Two research outcomes. Additionally, as seen in the respective studies' discussions, there is literature to support both similarities and differences among AES-holistic, AES-Rubric, and instructor grading patterns. When considered separately, the results from Study One and Study Two suggest that the edX AES tool may not be a completely accurate and reliable tool for measuring student success on the writing assignments presented in these two MOOCs when compared to instructor grading. However, additional analyses for both Study One and Study Two revealed potential strengths of the AES system, such that either the AES-Rubric Total or AES-Holistic Total tended to be within one to two points of instructor grades. Overall, these results indicate a need for further analyses investigating specific algorithm scoring patterns on different essay aspects and rubric criteria.

This research suggests that, although statistically significant differences existed between instructor- and AES-grading for Study One and Study Two, the actual scores were often quite close. Consequently, depending on the intent of individual instructors for their chosen assignment, these systems may be more acceptable as a formative, as opposed to summative, assessment of student learning, as suggested by Shermis and Burstein (2003) and noted by Mahana, Johns, and Apte (2012). However, given these results, it is likely that instructors would not want to utilize this technology for high-stakes testing until further research and development of the tool is completed.

Limitations

Several limitations and recommendations based on the present studies should be noted. Though we have made some tentative comparisons between Study One and Study Two findings, the essay assignments were quite different in scope and subject. Due to these uncontrolled differences, we cannot make strong claims regarding clear reasons that account for statistical differences. More research is needed to determine the types of assignments that are most relevant for this scoring tool (length, topic, number of rubric categories, range of rubric scores, etc.). For the sake of comparability, future research may examine courses from more similar disciplines, with more similar assignments and grading scales, and may be useful with the integration of qualitative analyses. This research was ultimately limited by the number of courses using the AES tool in the fall of 2013, constraining the study to evaluate only two courses used in these studies. As such, though we sought to replicate findings between courses and assignments, we are not able to compare them directly. Overall, with the growing availability of MOOCs for certificates or course credit, researchers have called for clarification and validation of the assessments utilized for MOOC students (Liyanagunawardena, Williams, & Adams, 2013).

Further research is also needed to investigate instructor perceptions of AES systems, and their pedagogical benefits and challenges. Specifically, instructors in these studies noted some key issues with the AES system and calibration. For instance, instructors noted several instances of plagiarism, and were unable to assign zero scores to these essays without affecting the essay-calibration system. Perhaps most importantly, this research was conducted on a particular AES system utilized through the edX platform; consequently, results may not generalize to other AES MOOC systems currently being utilized, tested, and developed.

Despite study limitations, the current research highlights potentially helpful next-steps for the creation, integration, and use of AES systems in MOOCs. For instance, AES-developers may want to consider using these systems in conjunction with an anti-plagiarism tool to reduce inflated scoring by the AES system of plagiarized essays. Faculty may also be more willing to engage with AES systems that offer greater metrics and information on holistic versus rubric-scored systems, and how they correlate with instructor grading. Finally, the fact that AES and Instructor-essay grades did not correlate highly with grades on other course assessments raises questions about how learning is measured in a MOOC and which assessment types are best suited to measure achievement of learning outcomes. Future studies should also be conducted based on more similar assignments in related fields for direct comparability and grading studies, as well as incorporating qualitative research evaluating AI-assessment tools. There is a growing demand for authentic assessment of higher-level learning in MOOCs, and research addressing these key issues in AES-systems would contribute greatly to that increasing need in online learning.

Acknowledgement

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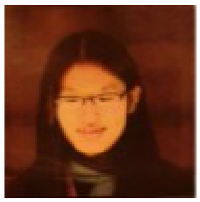
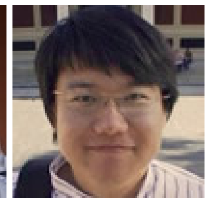
Influence of Incentives on Performance in a Pre-College Biology MOOC

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Abstract

There is concern that online education may widen the achievement gap between students from different socioeconomic classes. The recent discussion of integrating massive open online courses (MOOCs) into formal higher education has added fuel to this debate. In this study, factors influencing enrollment and completion in a pre-college preparatory MOOC were explored. University of California at Irvine (UCI) students of all preparation levels, defined by math Scholastic Aptitude Test (SAT) score, were invited to take a Bio Prep MOOC to help them prepare for introductory biology. Students with math SAT below 550 were offered the explicit incentive of an early change to the biology major upon successful completion of the MOOC and two additional onsite courses. Our results demonstrate that, among course registrants, a higher percentage of UCI students (>60%) completed the course than non-UCI registrants from the general population (<9%). Female UCI students had a greater likelihood of enrolling in the MOOC, but were not different from male students in terms of performance. University students entering with low preparation outperformed students entering who already had the credentials to become biology majors. These findings suggest that MOOCs can reach students, even those entering college with less preparation, before they enter university and have the potential to prepare them for challenging science, technology, engineering, and mathematics (STEM) courses.

Keywords: MOOCs; STEM; remedial course

Introduction

The demand for a diverse workforce of individuals with degrees in science, technology, engineering, and mathematics (STEM) has focused attention on how to increase the enrollment and retention of undergraduate STEM majors (National Science Foundation, 2004; National Science Board, 2006; Wilson et al., 2012; National Science Board, 2012). Attrition in STEM majors is particularly high during the first two years of undergraduate education (Seymour & Hewitt, 1997 ; Shuman et al., 1999; Chang, Cerna, Han, & Sàenz, 2008). At many universities, large introductory STEM courses, often referred to as "gate-keepers," represent major barriers that discourage students from entering or persisting in STEM disciplines. Moreover, females (Felder, Felder, Mauney, Hamrin, & Dietz, 1995; Brainard & Carlin, 1997; Blickenstaff, 2005), first-generation college students (Engle & Tinto, 2008), students from low-income families (Lam, Srivatsan, Doverspike, Vesalo, & Mawasha, 2006), and under-represented minority students (Cole & Espinoza, 2008) are more likely to drop out from STEM majors.

In recent years, with the number of college applications increasing (Clinedinst & Hawkins, 2014), there are growing numbers of low-income, under-represented minority, and first generation college students in entering classes. These students represent a tremendous resource for developing a diverse community of STEM graduates but they are also at high risk for dropping out since they are often academically under-prepared (Perna & Titus, 2005; Gumport, 2007; Breneman, Jr., & Hoxby, 1998). Providing these incoming students with access to low cost, high quality courses that help them transition to college and be successful in STEM majors is therefore of great importance. However, financial constraints have made it increasingly difficult for the brick-and-mortar campuses to provide transition face-to-face instruction to support these students (Clinedinst & Hawkins, 2014), especially in the summer before initial entry.

The emergence of massive open online courses (MOOCs) potentially affords universities the opportunity to provide students with preparatory courses before they enter university, at relatively low cost. MOOCs are typically developed by university faculty and are free for anyone who has access to a computer and the internet. In general, the completion rate of stand-alone MOOCs is very low (about 5%) (Ho et al., 2014). Enrollment surveys indicate that the students in the new massive courses are largely male and well-educated learners, rather than the underserved (Christensen et al., 2013). A pilot study conducted in San Jose State University, which introduced MOOCs into the curriculum, reported that matriculated students performed better than non-matriculated students. However, the completion rate of the specifically targeted at-risk students was disappointingly low. It was reported that students' effort was the strongest indicator of their success in the course (Firmin et al., 2014). In addition, students claiming a high intention to complete a MOOC in a pre-survey are much more likely to finish the course than others (Koller et al., 2013). This raises the question of whether it is possible to increase learners' motivation, engagement, and success in MOOCs by providing external incentives.

The goal of this study was to develop a course that would help under-prepared students who had been accepted to the UCI gain skills and knowledge that would increase their probability of success in a large freshman STEM course, Bio 93. We chose to develop this as a MOOC to determine if this could be done in the context of a course that would also potentially benefit a broad group of individuals in the general population. We first introduce the rationale for providing this course, explain how it was organized, and describe the incentive offered to increase motivation for under-prepared students, and then analyze the extent to which the course achieved our goals.

Research Questions

The study addresses the following questions.

1. How did UC Irvine (UCI) Bio 93 students perform in the MOOC compared to the general population students?

2. Among UCI Bio 93 students, were underprepared students more likely to enroll in the MOOC given an explicit incentive?

3. Among UCI Bio 93 students, were underprepared students more likely to complete the course?

This paper focuses on student success within the Bio Prep MOOC; a second paper will focus on the performance by students in the subsequent face-to-face Bio 93 course.

Data and Methods

Pre-College Biology MOOC Design

At UCI, Bio 93 is the first-quarter, introductory biology course that is required for all students majoring in biology or health careers. Author Diane K. O'Dowd has been teaching the class for 10 years, and author Adrienne E. Williams has worked with Diane K. O'Dowd to develop teaching techniques and measure student performance in the course for the past 8 years. Our analysis of data from the last three years indicates that Bio 93 is a major obstacle for under-represented minority students. The drop/fail rate for these groups in Bio 93 is 25-30%, much higher than the 15% overall class average. Further analysis of learner outcome data indicates that high school preparation is a critical factor in passing Bio 93. A high percentage of students who score below 550 on their quantitative Scholastic Aptitude Test (SAT) scores drop or fail Bio 93. Students must score 550 or above to be accepted as a biology major; those below that score are redirected into other majors, most commonly undecided/undeclared.We have investigated ways of creating preparatory courses and learning tools to meet the needs of academically less prepared students, ideally before they enter the university. Online courses offer one way of potentially helping students who have not yet moved to Irvine, and free courses are potentially highly beneficial for this often low-income group. The Bio Prep MOOC was designed by the co-first author Adrienne E. Williams to be accessible to the general public, but was specifically aimed at providing knowledge and critical thinking that is important for success in Bio 93. It was offered on the Coursera MOOC platform.

The MOOC consisted of three modules with the biological themes of membrane transport, protein synthesis and localization, and neurophysiology. Authors Adrienne E. Williams and Diane K. O'Dowd taught the course as two tracks. The Basics track was based on content videos and quizzes only. To complete the Scholars track, students needed to compose written responses to three to five short-answer questions in each of the three units of the course, and provide peer assessments (both numerical scores and comments) on short answers of at least three peers for each question. The Scholars Track also included three independent study projects, where students were required to apply what they have learned from the lectures to new situations. Students were also expected to participate in peer assessment of other students' project reports to receive a grade for their own report. These additional writing and peer assessment activities were included in the Scholars track based on prior research indicating a correlation with academic success (Liang & Tsai, 2010). Students who successfully completed the Scholars track were awarded a Distinction certificate and those who completed the Basics track were awarded a Normal certificate. Students did not need to pre-select a track but were given the appropriate certificate based on the tasks they fulfilled. In summary, the Scholars track requires more self-regulated study for students than the Basics track.

UCI Student Participation in the MOOC: Incentive for Underprepared Students

Like all Coursera courses, Bio Prep was offered to the general public, and approximately 37,000 students signed up. Beyond this general enrollment, we conducted targeted outreach for Bio Prep to incoming freshman students during summer Enrollment in early summer 2013, focusing on two groups in particular. Students accepted into the university as Biological Science majors were told about the course by the Biological Science counselors. They were encouraged to participate to help prepare them for a successful first quarter of Bio 93 but there was no explicit incentive. Another group of students applied to UCI with Biological Sciences as their first choice of major, but this choice was not granted because their math SAT scores were less than 550. Most of these students became Undecided majors. These students were also encouraged to participate in the Bio Prep MOOC by their Summer Enrollment counselors through the Undecided Student Affairs Office and they were additionally provided an explicit but no cost incentive to take the MOOC. Ordinarily, students below the 550 math SAT threshold must complete a full year of biology and chemistry courses successfully before entering the Biological Sciences major. However, students below this threshold were informed that they could transfer to the major after only one quarter if they successfully completed the Bio Prep MOOC Scholars track and passed both Bio 93 and introductory chemistry during fall quarter.

The MOOC was taught by Adrienne E. Williams and Diane K. O'Dowd in the four weeks immediately before fall quarter began at UCI (August 26 to September 23, 2013) to maximize the number of entering UCI students who could take the course.

Subjects

Subjects in the study included 27,487 MOOC students who had grade records in the Bio Prep MOOC, and the 1,695 UCI students who enrolled in Bio 93 in the fall 2013 quarter and for whom we had complete prior academic records. A subset of students were in both groups (n = 382). This subset was further divided into the "strong math UCI" students (n=226), who had SAT scores of 550 or higher, and the "weak math UCI" students (n=156), who had SAT scores under 550.

Dataset

Data for the study came from three sources. The first is the SQL file extracted from Coursera database, which includes students' assignment performance (e.g., quiz and peer assessment) and final performance in the Bio Prep MOOC (e.g., successfully completed the Scholars track and receiving the Distinction certificate). About 37,933 students enrolled in the Bio Prep MOOC and 27,487 students had grade records. A total of 551 students earned the Distinction certificate and 1,971 students earned the Normal certificate.

The second source of data comes from UCI's Office of Institutional Research, which provides the demographic information and pre-college academic preparation record (i.e., SAT scores) of students who enrolled in the onsite Bio 93 course.

Also, for UCI Bio 93 students who participated in the Bio Prep MOOC, we have the above data associated with their Coursera e-mail address and their UCI identification information.

Student Information

All MOOC participants (n=27,487) were coded as either UCI students (382) or non-UCI students (27,105). For all UCI Bio 93 students (n=1,695), including those in the MOOC, we gathered SAT math, reading, and writing scores. Literature indicates that online education may widen the academic performance gap between traditionally low-performing students and high-performing students (Xu & Jaggars, 2013). This study therefore examines how students' previous academic performance influences their participation and performance in the MOOC. Students were also coded as "weak math" if their math SAT scores were below 550. As SAT math 550 is a threshold for the university incentive policy, this variable reflects the effect of an explicit incentive policy on students' participation and performance in the Bio Prep MOOC.

Each UCI student was identified by gender and ethnicity. Prior studies show contradictory results in terms of which gender is more likely to take online courses and perform better in online learning. The analysis of University of Pennsylvania's 36 MOOCs indicates that there are significantly more males than females taking MOOCs (Christensen et al., 2013). Some research on distance education shows that there is no gender difference in learning outcomes in online learning while some research indicates that females perform significantly better than males (Xu & Jaggars, 2013). It has been argued that females are more motivated and better at communicating and at scheduling their online learning (McSporran & Young, 2001). Ethnicity was coded as under-represented minority (URM, i.e., Black/African-American, American Indian, and Hispanic) or non-URM. A number of studies report that the educational gap between URMs and non-URMs is wider in online courses than in face-to-face courses (for an overview, see Means, Bakia, and Murphy, 2014).

Analyses

To analyze the first research question, we present a descriptive assessment of UCI Bio 93 freshmen's MOOC performance compared to the other MOOC participants. To analyze the second and the third research questions, we construct a logistic regression model and a multinomial logistic regression model to investigate the factors that influence UCI Bio 93 students' enrollment and final performance in the MOOC separately.

Results

There were differences in performance in the MOOC between the three groups examined: strong math UCI students, weak math UCI students and non-UCI MOOC participants. Typical of many MOOCs, the completion percentage of non-UCI participants was low, with 92% not completing. Of those that completed, approximately 7% earned a Normal certificate and <2% earned Distinction (Figure 1). In marked contrast, the two groups of UCI students had a much higher percentage of completion and Distinction. For the strong math UCI students only 36% did not complete the course, while 37% earned a Normal certificate and 27% earned a Distinction certificate (Figure 1). The percentage of weak math UCI students (n=156) that did not complete the course (31%) was similar to the strong math group, but more earned a Distinction certification (39%) than a Normal certificate (30%) (Figure 1).

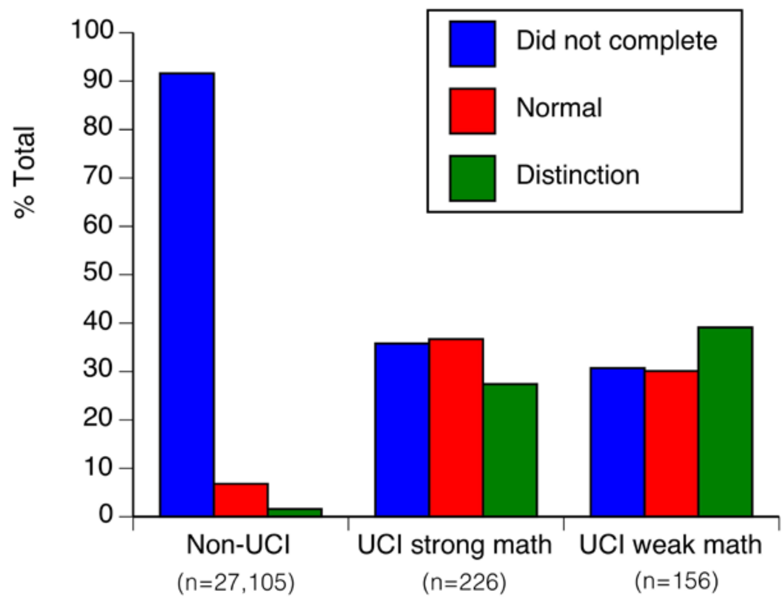

Figure 1. MOOC completion and performance by group. Percentage of total students within each group who did not complete the course, completed the course and earned a Normal certificate, or completed the course and earned a Distinction certificate. Total number in each group indicated (n).

Research Questions 2 and 3 focus on which UCI students enroll in and complete the MOOC.

MOOC Enrollment

Table 1 shows the odds ratios from the nested logistic regression models predicting UCI Bio 93 students enrolled in the Bio Prep MOOC, using data from the entire cohort of Bio 93 students. As our hypothesis predicted, we found weak math students are more likely to enroll in the course. However, when we control for gender the effect of math is not significant. This indicates that women are more likely to enroll in the MOOC than men. There was no effect of ethnicity on enrollment.

Table 1

Odds Ratios From Logistic Regression Models Predicting MOOC Enrollment

	Model1 Enrollment	Model2 Enrollment	Model3 Enrollment	Model3 Enrollment
Weak Math	1.319*	1.433**	1.355*	1.261
	(2.32)	(2.66)	(2.23)	(1.63)
SAT Reading		1.000	1.001	1.001
		(0.37)	(0.67)	(0.50)
SAT Writing		1.001	1.000	1.001
		(0.60)	(0.25)	(0.47)
Female			1.604***	1.594***
			(3.52)	(3.47)
Minority				1.263
				(1.73)
N	1695	1693	1693	1693
R^2	0.003	0.004	0.011	0.013

Notes. Exponentiated coefficients; t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

MOOC Completion

We hypothesized that students with weak math SAT scores would be more likely to complete the MOOC with distinction, given the incentive provided by the university. As predicted, the probability of obtaining the Distinction certificate for students with low SAT math was about 1.66 times greater than the high SAT math students (Table 2, Model 1). This effect remains when the model controls for student preparation, gender and ethnicity. None of the other student characteristics examined significantly affected the prediction of earning a Normal certificate.

Table 2

Multinomial Logistic Regression Predicting UCI Bio 93 Students' MOOC Performance

	Model1 Performance	Model2 Performance	Model3 Performance	Model4 Performance
Distinction				
Weak Math	1.660*	1.720	1.761	1.995*
	(1.98)	(1.76)	(1.83)	(2.12)
Sat Reading		1.002	1.002	1.003
		(0.88)	(0.87)	(1.04)
Sat Writing		0.999	0.999	0.998
		(-0.58)	(-0.50)	(-0.74)
Female			0.793	0.796
			(-0.74)	(-0.72)
Minority				0.680
				(-1.28)
Normal				
Weak Math	0.956	0.667	0.712	0.680
	(-0.18)	(-1.34)	(-1.11)	(-1.20)
Sat Reading		0.995	0.995	0.995
		(-1.79)	(-1.81)	(-1.86)
Sat Writing		0.999	1.000	1.000
		(-0.32)	(-0.12)	(-0.02)
Female			0.574	0.578
			(-1.86)	(-1.84)
Minority				1.158
				(0.50)
N	382	382	382	382
R^2	0.007	0.022	0.026	0.030

Notes. Exponentiated coefficients; t statistics in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Discussion

Our results demonstrate that the percentage of UCI students completing the MOOC and earning Distinction was much higher than the non-UCI MOOC students. Female students were more likely to enroll than male students, and low math SAT students were more likely to earn Distinction.

There would be little support for investing in development of college preparatory classes if the completion rates are similar to those reported for most MOOCs (~5%) (Ho et al., 2014). A study at San Jose State University indicated that students in a MOOC who are also matriculated and the course counts for university credit have a higher completion rate in three courses (29.8%, 50.0% and 54.3% respectively) than those who are not matriculated (17.6%, 11.9% and 48.7% respectively; Firmin et al., 2014). Our study demonstrates the completion rate for incoming UCI students in a biology prep MOOC can be boosted to over 60% even when there is no course or university credit involved. The exposure to knowledge and/or skills relevant to a first quarter class was sufficient to result in this increase since incoming 1st year students with the credentials to become biology majors completed at approximately the same rate as underprepared students who were given an explicit incentive.

There is considerable concern that online education programs, while effective for some, may amplify rather than narrow educational and social divides (Bolt & Crawford, 2000). Some quasi-experimental studies show that online education reflects the same divide commonly observed in the brick-and-mortar settings. For example, Black and Hispanic students performed more poorly than White students in online courses (Newell, 2007). In an experimental study involving multiple sections of an economics course no significant difference was found between online and lecture courses among students with higher prior GPA; however, among students with lower GPA, online students scored significantly lower than face-to-face lecture students (Figlio, Rush, & Yin, 2010). In the San Jose State University study, the low course pass rates may be due to the target group being at-risk students (Firmin et al., 2014).

In the present study we found that UCI incoming students with weak SAT math skills had a higher probability of completing the MOOC with Distinction than students with strong math skills. It is likely that this difference in completing the MOOC with Distinction is associated with the incentive policy enacted for incoming freshmen who did not meet the SAT math requirement for a biology major. This provided freshmen who obtained a Distinction certificate the opportunity to enter the biology major two quarters earlier than those who did not complete or earned only a Normal certificate. Importantly this incentive did not result in any costs for the students, the instructors, or the university.

Our results also indicate that among UCI students, females were more likely to enroll in the MOOC than male students. This is interesting given previous research showing that the majority (51%~87%) of MOOC population are males (Ho et al., 2014) and it is potentially important given the underrepresentation of women in many STEM fields (Beede et. al, 2011) and women's greater likelihood to transfer out of STEM majors (Chen & Soldner, 2013). One possible interpretation, consistent with a recent study, is that female students are more motivated and adaptive to online education than male students in an educational setting (Xu & Jaggars, 2013). In contrast, unlike the Xu and Jaggars study, we did not find negative associations between ethnicity and enrollment or performance in the MOOC.

Although previous literature shows that low performance students can be further disadvantaged by online education, our results suggest that a MOOC with no-cost incentives provides an additional learning opportunity for low-performance students.

Follow-up research will analyze the impact of the MOOC for students' academic performance in the onsite Bio 93 course. Additional studies from other institutions and MOOCs will also be important in evaluating the effectiveness of MOOCs as preparatory courses for higher education.

Acknowledgements

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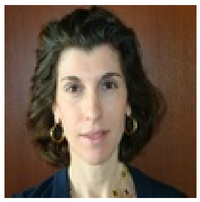
Resource Requirements and Costs of Developing and Delivering MOOCs

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Abstract

Given the ongoing alarm regarding uncontrollable costs of higher education, it would be reasonable to expect not only concern about the impact of MOOCs on educational outcomes, but also systematic efforts to document the resources expended on their development and delivery. However, there is little publicly available information on MOOC costs that is based on rigorous analysis. In this article, we first address what institutional resources are required for the development and delivery of MOOCs, based on interviews conducted with 83 administrators, faculty members, researchers, and other actors in the MOOCspace. Subsequently, we use the ingredients method to present cost analyses of MOOC production and delivery at four institutions. We find costs ranging from $38,980 to $325,330 per MOOC, and costs per completer of $74-$272, substantially lower than costs per completer of regular online courses, by merit of scalability. Based on this metric, MOOCs appear more cost-effective than online courses, but we recommend judging MOOCs by impact on learning and caution that they may only be cost-effective for the most self-motivated learners. By demonstrating the methods of cost analysis as applied to MOOCs, we hope that future assessments of the value of MOOCs will combine both cost information and effectiveness data to yield cost-effectiveness ratios that can be compared with the cost-effectiveness of alternative modes of education delivery. Such information will help decision-makers in higher education make rational decisions regarding the most productive use of limited educational resources, to the benefit of both learners and taxpayers.

Keywords: Online learning; higher education

Introduction

At least since the 1990s concerns have arisen over the increasing costs and decreasing productivity of higher education, with technology-based reforms being promoted as a solution for institutions of higher education (IHEs) struggling to educate larger numbers of students with a wider range of incoming preparation and learning styles (e.g., Twigg, 1992; Rumble, 1997; Bowen, 2012, 2013; Barber, Donnelly, & Rizvi, 2013). Established IHEs have generally been slow to take advantage of technology to improve productivity in the delivery of education (Miller, 2010), for reasons that are more often "psychological, political, and cultural" rather than "conceptual, technical, or economic" (Dede, Ed., 2013, p. 52). However, a few pioneering institutions and numerous newcomers have gained traction swiftly by offering online or blended learning opportunities to both typical college-aged students and to older, non-traditional learners. As early as the 1970s, the Open University in the United Kingdom was able to offer distance education courses at a large enough scale to render institutional costs per student below the costs of similar courses at traditional campuses (Laidlaw & Layard, 1974).

There is, however, limited evidence regarding the costs of technology-mediated distance instruction and mixed evidence as to whether it lowers the overall costs of education or increases them. Lack (2013) observes that inattention to costs is pervasive in postsecondary education, and highlights one of the few exceptions in the field of postsecondary online learning, the National Center for Academic Transformation (NCAT), which, according to its website, helps institutions use "information technology to re-design learning environments to produce better learning outcomes for students at a reduced cost to the institution." Miller (2010) reports cost savings of 13%-77% across fifty instances of NCAT-supported course re-designs. Costs per student averaged $196 across the fifty original, traditional versions of the courses while the versions that were re-designed with technology components averaged 39% less, at $119 per student. In one example, costs per student for a fine arts course offered by Florida Gulf Coast University dropped from $132 to $70 after it was transformed from an on-campus course into a fully online course. It is not clear, however, what method was used to establish costs or which personnel and other resources were included in the cost calculations. Twigg (2003) acknowledges that the NCAT estimates do not include costs of course development and transition from traditional to re-designed version, but she also argues that they do not reflect savings that can be achieved by increasing retention, reducing space utilization, or eliminating similar courses.

Cota, Jayaram, and Laboissière (2011) assert that the most productive colleges in the United States (U.S.), as defined by cost per degree (institution's total annual costs divided by the number of degrees awarded) achieve their efficiencies through five strategies, one of which is keeping costs under control by re-designing instruction, often using technology to deliver some or all content and instruction at distance. On the other hand, Means, Bakia, and Murphy (2014) assert that online learning incurs greater investment costs than conventional instruction for program design, curriculum development, and development or selection of digital resources. Given the high fixed costs of development of online instruction, and of technology-mediated distance education more generally, many experts argue that scale is essential to reducing costs per student (e.g., Boeke, Ed., 2001; Jones, 2004). Massive open online courses (MOOCs) would appear to offer the ideal opportunity to take advantage of scale given their potentially enormous enrollments.

Online enrollment in the U.S. has grown at a rate between 6.1% and 36.5% in each year since 2002 (Allen & Seaman, 2013, 2014), and over the past two years MOOCs have begun to play a noticeable role in this growth. In 2013, 5% of 2,831 IHEs responding to Allen and Seaman's (2014) annual survey about online learning were offering a MOOC, 9% were planning to do so, and 53% were undecided as to whether to engage in this innovation. While it is clear that MOOCs have "... nudged almost every university toward developing an Internet strategy" (Lewin, 2013), there is little evidence that MOOCs have, as yet, contributed to lowering the costs of higher education.

Given the continuing alarm regarding uncontrollable costs of higher education (e.g., Bowen, 2013; Kelly & Carey, Eds., 2013), it would be reasonable to expect not only concern about the impact of MOOCs on educational outcomes, but also systematic efforts to document the resources expended on their development and delivery. However, beyond the approximate estimates offered by Boddy et al. (2013), there is little publicly available information on MOOC costs that is based on rigorous analysis. Ithaka S+R (2014) documents hours spent by personnel in developing and delivering hybrid courses at the University System of Maryland, some of which integrated MOOCs or MOOC components, but does not translate these into costs.

Moreover, it appears that lowering costs is not the highest priority for MOOC initiatives: among the 140 or so IHEs offering MOOCs in Allen and Seaman's (2014) sample, less than ten indicated that exploring cost reductions was an objective for their MOOC initiatives. Hollands and Tirthali (2014) found that, of 29 institutions offering MOOCs, improving economics was a goal for only 38%. A recent poll by the Alliance for Higher Education and Democracy (AHEAD) at the University of Pennsylvania found that, among the approximately 44 respondents at institutions offering a MOOC, only 19% strongly agreed that MOOCs may be an effective mechanism for reducing costs of higher education (AHEAD, 2014). Goals that were as or more important than reducing costs to the IHEs in these studies included: increasing access to education, raising institutional visibility or building brand, increasing student recruitment, and improving or innovating pedagogy.

Ruth (2013) explores the question of whether MOOCs can be used to help reduce college tuition and concludes that MOOCs may only contribute to lowering costs of higher education if combined with a reduction in labor costs, as experienced in successful implementations of NCAT's course re-design model. Hoxby (2014) assesses the economic value of MOOCs and questions the assumption that cost reductions, via economies of scale, will be realized through MOOCs because she expects that the most popular MOOC instructors will eventually need to be paid high salaries. It is perplexing that MOOCs have taken hold without much evidence as to whether they are effective in improving participant skills and knowledge, and without a firmer idea of their economic value, resource requirements, and costs. As Means et al. (2014) observe, “Both irrational exuberance and deep-seated fear concerning online learning are running high” (p. 42). If decision-makers are to make rational decisions about engaging in MOOC production, it is critical to know whether MOOCs are both effective and cost-effective in delivering quality education or related outcomes.

In this article, our objectives are to address what institutional resources are required for the development and delivery of MOOCs, what are the associated costs per MOOC and, where the data are available, what is the cost per MOOC completer. We compare these findings with costs of other online and distance learning to assess whether MOOCs can deliver education more inexpensively at scale than alternative options. We hope that by demonstrating the methods of cost analysis as applied to MOOCs, future assessments of the value of MOOCs and other distance learning courses will combine both cost information and effectiveness data to yield cost-effectiveness ratios that can be compared with the cost-effectiveness of alternative modes of education delivery. Such information will help decision-makers in higher education make rational decisions regarding the most productive use of limited educational resources, to the benefit of both learners and taxpayers.

Methods

To elicit information regarding the resources required to develop and deliver MOOCs, we conducted a qualitative study (see Merriam, 2009) similar to that employed by Bacow, Bowen, Guthrie, Lack, and Long (2012) in their investigation of barriers to online learning in higher education. We interviewed 83 individuals across 62 public and private organizations including IHEs, research organizations, online learning platform providers, other for-profit education companies, and several additional stakeholders in the online learning space. Table 1 indicates the distribution of interviewees across institutional type. Thirty of our interviewees were administrators at IHEs, 22 were faculty members, 16 were executives at other institutions, 13 were researchers, one was an educational technologist, and one was a program officer at a foundation.

Interviewees were identified by reviewing the academic and journalistic literature on MOOCs, the names of presenters and panelists at conferences on MOOCs or online learning in higher education, and the MOOC activities of institutions on the Internet. Many of our interviewees suggested other people for us to interview either at their own institutions or elsewhere. We contacted by e-mail individuals who appeared to be knowledgeable about MOOCs or online learning based on their position in deciding whether and how to engage with MOOCs, experience teaching or planning MOOCs, or relevant research and publications.

We contacted 100 individuals on a rolling basis at 66 different institutions, 39 of which were IHEs. Most interviewees were based in the U.S., two were in China, two in the United Kingdom, and several were in Canada. Interviews were conducted between June

2013 and February 2014 and follow-ups by e-mail with interviewees to obtain updates and to verify information continued until May 2014. Almost half of the interviews were conducted face-to-face with the remainder conducted by telephone or Skype. Interviews averaged 75 minutes in length and followed a semi-structured interview protocol (see Merriam, 2009). Most interviewees agreed to be recorded, and the digital audio-files were subsequently transcribed. All interview notes and transcriptions were coded (LeCompte & Schensul, 1999) in NVivo software using themes initially derived from the interview protocol and iteratively refined as more granular topics were identified.

Table 1

Institutional Affiliations of Interviewees

Type of institution	Number of institutions represented*	Number of interviewees
Public universities	16	20
Private universities	14	26
Community colleges	9	10
Platform providers	5	6
Research organizations	7	8
Other for-profit education companies	4	5
Other institutions**	7	8
Total	62	83

* One person was interviewed at most institutions, but at a few institutions several individuals were interviewed, for example, to include administrators, faculty members, and researchers.
**Other institutions: museum, K-12 school district, educational technology advocacy group, higher education association, venture capital firm, private foundation, independent consultant.

Cost analyses were conducted using the ingredients method (Levin & McEwan, 2001) to estimate the costs of MOOC production and delivery at four of the institutions where we were able to obtain adequate data on resource use. We estimated costs for one connectivist MOOC (cMOOC) and seven xMOOCs. We focused on estimating personnel costs and assumed these would represent 75% of total costs, based on Levin and McEwan's assertion that personnel costs typically account for 70-80% of total costs of educational interventions (see p. 53). We do not estimate costs individually for facilities, other equipment, and overhead but assume they amount to 25% of total costs. To estimate personnel costs we asked our interviewees detailed questions regarding role, qualifications, and hours spent by each person involved in MOOC development and production. In two cases, detailed records of time spent were collected by the institutions as part of their regular project management process. In one case, the MOOC instructor logged time spent on the MOOC on a daily basis and we obtained other personnel hours by interviewing the relevant individuals shortly after the conclusion of the MOOC. In the case of the cMOOC, we obtained retrospective estimates of hours spent from the two instructors involved. We expect greatest accuracy when time spent is logged on a regular basis.

In order to assign costs to personnel time, we used national average U.S. salaries for individuals in each relevant job category, as opposed to using actual salary levels of personnel at each specific institution, except in one case where some of the personnel costs were given to us directly. This approach not only respects the privacy of the individuals involved, but, more practically, allows for a comparison of the costs across a number of institutions without introducing local pricing influences. National average prices and benefits rates were obtained from the CBCSE Database of Educational Resource Prices which relies on multiple national surveys such as the National Compensation Survey, U.S. Department of Labor. Cost calculations were executed using the CBCSE Cost Tool Kit, an Excel-based application designed for the purpose of estimating costs of educational programs.

Findings

Resource Requirements for Developing and Delivering MOOCs

We first review the resources required to produce and deliver MOOCs based on information provided by our interviewees. Subsequently, we present our estimates of the costs of MOOCs from the perspective of the producer (i.e., the college, university, or museum, as opposed to the platform provider or participant). We note that for MOOCs that are delivered via third-party platforms, there are often significant, additional costs to the platform provider which may be passed on to the MOOC producers through a direct charge for the platform services or a revenue-sharing agreement (see Young, 2012; Kolowich, 2013).

The major cost drivers we identified in MOOC production and delivery were: the number of faculty members, administrators, and instructional support personnel participating in the process; the quality of videography; the nature of the delivery platform; programming for special features such as computer code auto-graders, virtual labs, simulations, or gamification; analysis of platform data; and technical support for participants. MOOC production teams that were described to us seldom included fewer than five professionals and, in at least one instance, over 30 people were involved.

All interviewees who had been involved in the development of a MOOC reported the effort being two to three times greater than creating a traditional course. These reports comport with written accounts such as Cima's (2013). Instructors typically spent several hundred hours over several months preparing and re-purposing course materials, and practicing lecture delivery prior to video-taping; several days on actual shoots; and one to two days reviewing the finished video. To create one hour's worth of MOOC video-lecture required three to ten hours of preparation according to several faculty members, the lower end of the range being in instances where the materials were being re-purposed from existing lectures. To create ten minutes of voice-over-PowerPoint video required six to eight hours according to an interviewee at a private university.

Development of MOOCs was deemed to be more time-consuming compared to traditional online courses due to MOOC-specific components such as high quality video, quizzes to substitute instructor-graded assignments, and peer-to-peer learning technologies. Several interviewees noted that the level of “polish” required for content and delivery was far greater than for traditional on-campus or online courses because of the more public nature of the MOOC. A number of interviewees likened the effort involved in creating a MOOC with writing a textbook in a team. At some institutions faculty members were granted a course release and/or paid stipends ranging from $3,000-$15,000 for developing and delivering a MOOC, but the opportunity costs of the instructor’s time are likely to be higher in many instances. We frequently heard estimates in the order of 400 hours of faculty member time per MOOC developed, the equivalent of 26% of an academic year.

In addition to the direct costs of producing and delivering MOOCs, many of our interviewees provided insights into a plethora of additional considerations for institutions engaging with MOOCs. For example, MOOCs can only attract massive audiences if they are sufficiently marketed. While the platform providers such as Coursera, edX, and Academic Partnerships fulfill these marketing and communications functions for their partner institutions, those institutions using more “do-it-yourself” platforms must find suitable advertising channels. Computing and Internet services for on-campus students participating in MOOCs may need to be increased or upgraded, for example, help desk support and retrofitting buildings to provide enough bandwidth capacity for many students to simultaneously stream or download video. Institutional websites and learning management systems need to provide an access point to relevant MOOCs. Cheal (2012) documents many of these issues as encountered by San José State University’s MOOC initiatives.

A variety of administrative offices are likely to be involved in activities such as obtaining copyright permissions and establishing contracts between the institution and online platform provider, and between the institution and its faculty members to address intellectual property rights, revenue sharing, faculty compensation and workload issues. Compliance with disability regulations in MOOCs must be regularly audited and enforced, and accommodations made, for example, extra time on quizzes and exams for students with learning disabilities. For institutions providing credit for MOOCs, the student admissions, registration, billing, authentication, and crediting systems need to be aligned with platform enrollment procedures. If prerequisites are required for credit-earning participation in a course, a system must be developed to handle large numbers of students.

Costs of MOOC Production and Delivery

Based on the cost analyses we conducted of MOOC production and delivery, we estimated personnel costs ranging between $29,000 and $244,000 per MOOC, depending on the number of people involved in the process, the amount of time dedicated, and the quality of video production. The costs of the platform, captioning, content hosting, and analysis of user data to populate the data dashboard were assumed by Coursera for all xMOOCs we analyzed. We estimate total costs per MOOC, including facilities, equipment, and overhead, of $38,980 to $325,330 (see Table 2). In two cases where course completion data were available, we present a cost per completer. Details of each institution's MOOC(s) and our related cost analysis are presented below.

Table 2

Estimated Costs of MOOC Production and Delivery at Four Institutions

Institution	Type of MOOC	Length of MOOC (weeks)	Total estimated costs per MOOC	Costs per completer
Teachers College, Columbia University	xMOOC	8	$38,980	$74
University of Manitoba	cMOOC	12	$65,800 - $71,800	-
American Museum of Natural History	xMOOC	4	$104,620	$272
Large Midwestern university	xMOOC	5-8	$203,770 - $325,330	-

Cost analysis for development and delivery of Connectivism and Connected Knowledge (a cMOOC).

Connectivism and Connected Knowledge (CCK08), the first course to be dubbed a "MOOC," was developed and delivered in 2008 by George Siemens and Stephen Downes. The 12-week course was offered at the University of Manitoba to 25 enrolled students for fee and for credit and also as a free, non-credit-bearing course to 2,300 other participants (Downes, 2008). The course has been re-run three times since.

Siemens estimated the time burden for CCK08 development and delivery as follows: 100-150 hours on course design and development over a two month period; 70 hours per week on course delivery for the first two to three weeks (interacting with students and posting on discussion forums or writing blog posts to summarize discussion and activities), tapering down to 30 hours per week in the twelfth week. At the lower end of Siemens' estimates, the total number of hours amount to 715. At the high end, they amount to 770. We estimate costs at each end of the range.

Downes estimated his total time commitment for CCK08 at 88-108 hours: 20-40 hours in programming time to make adjustments to the gRSShopper course aggregation software that he had developed over many years; 20 hours setting up the course website; and four hours per week during course delivery to maintain the site and prepare audio archives. No technology support personnel, learning designers, or teaching assistants (TAs) were utilized in the development and delivery of CCK08.

Using U.S. national average salary and benefits rates for public postsecondary faculty members and public sector research scientists, the costs of personnel time to replicate *CCK08* ranges from $49,400 to $53,800 and we estimate the total costs of between $65,800 and $71,790, as shown in Table 3.

Re-runs of CCK08 required less design and development time. Additionally, with better course management software, weekly delivery time for the 2012 delivery fell to 30-40 hours per week for the first two to three weeks. Some repeat students self-selected as TAs and reduced the instructors' time burden by helping manage the forums, responding to inquiries, and providing guidance to new students. Set-up time for the course website dropped from 20 hours to four hours. For Siemens, we estimate the total time commitment for a CCK08 re-run at 284 hours: 20 hours to "refresh" the course design and resources before a new launch; 28 hours per week in delivery for the first three weeks; and 20 hours per week in delivery for the remaining nine weeks. For Downes, we estimate the total time commitment for a CCK08 re-run at 72 hours: four hours for website set-up; 20 hours to adjust gRSShopper to accommodate new tools; and four hours per week to maintain the course site. The possible range of time committed by the self-selected TAs could be very wide. We use an estimate of 350 hours total, under the assumption that the TAs collectively replace the reduced hours in Siemens' delivery time. Total estimated costs for the re-run are $40,740, 38% lower than the low estimate for the first run.

Table 3

Estimated Costs for the First Run of CCK08 and Re-run

Ingredient	First run low estimate	First run high estimate	Re-run estimate
Instructor 1	$44,756	$48,199	$17,777
Instructor 2	$4,597	$5,642	$3,761
TAs	-	-	$9,015
Facilities, equipment, overhead	$16,451	$17,947	$10,184
Total	$65,804	$71,788	S40,737

Sources: George Siemens, formerly at Athabasca University, and Stephen Downes, National Research Council.

Costs of xMOOC production at a large midwestern university.

Before its recent entry to the MOOCspace, this university, which requested partial anonymity, had already established an infrastructure for the development of online courses. In 2013, a small number of faculty members were invited to develop and deliver five- to eight-week MOOCs, primarily to showcase the university and engage new audiences. Each faculty member was assigned a design and support team of five to six people to help in the design and production of the MOOC, including a project manager, instructional designers, instructional technologists, and a liaison to the video production team. Additional personnel supervised the design and support teams, and provided programming capacity, overall project management, evaluation, and administrative services.

As a routine part of the project management function at this university, detailed time logs are kept by each design team member so that costs for these personnel can be tracked accurately. We used the cost estimates provided by the university for these personnel in our analysis because we did not obtain enough detail regarding these personnel ingredients (e.g., specific role, level of experience, highest degree of education) to allow us to assign prices ourselves. Faculty member and TA time were not logged but we obtained estimates either during or after MOOC production and assigned relevant costs ourselves, using national average salary and benefits rates for postsecondary public institutions. For the first three MOOCs created and delivered, the hours spent per MOOC by various personnel were as follows: 200-500 hours for the MOOC design team, 700-900 hours for the video production team, 150-155 hours for technical support, 90-220 hours for the faculty member, and 650 hours for a TA in one MOOC. Total personnel hours were 1,140 for the least time-intensive MOOC and 2,245 for the most demanding MOOC. The resulting cost estimates are shown in Table 4.

Table 4

Range Of Estimated Personnel Costs Per MOOC for Design, Production, and Delivery at a Large Midwestern University

Type of personnel	Low	High
Design and support team	$70,000	$125,000
Computer programming unit	$0	$15,000
Management (avg. across 3 MOOCs)	$77,200	$77,200
Faculty member	$5,630	$13,770
TA	$0	$13,029
Total personnel costs	$ 152,830	$244,000

Source: Evaluator at a large midwestern university.

The faculty time burden was relatively low because the dedicated design and support team took on much of the task of course design and development. Design team time varied depending on the complexity of the learning activities. We estimate the total costs per MOOC at $203,770 - $325,330. Salary levels at this geographical location may be lower than national averages so that costs for the non-teaching personnel could be higher on a national average basis, in the order of a few thousand dollars.

American Museum of Natural History MOOC initiative: resource requirements.

Between September and December 2013, the American Museum of Natural History (AMNH) delivered three four-week long MOOCs targeted at science educators. Planning efforts began in Spring 2013 and involved a team of museum professionals who had significant previous experience in developing and delivering online education. The core MOOC production team comprised a project director, a project manager, an in-house video producer, an educational technologist, and a senior administrator who also served as one of the MOOC instructors.

Table 5

Hours Spent by AMNH Personnel to Develop Three MOOCs

Personnel ingredient	Hours
Senior management	125
Project director	454
Project manager	980
Instructors	910
Educational technologist	174
TA	400
Evaluation expert	16
Graphic designer	350
Video producer	293
Video shooter	63
Video editor	210
HTML writer	30
CSS writer	10
Legal personnel	13
Marketing personnel	12
Business manager	5
Total for 3 MOOCs	4, 045
Hours per MOOC	1,348

Sources: Dr. Ro Kinzler, Senior Director, Science Education, AMNH; Dr. Robert Steiner, Director, Online Teacher Education Programs, AMNH; Maria Janelli, Senior Manager, Online Teacher Education Programs, AMNH.

While the museum had already previously developed many digital resources including science-content videos and educational essays on science topics, MOOCs presented a new challenge to develop lecture-based videos with "talking heads" or voice-over PowerPoint presentations, multiple-choice quizzes, peer-graded assessments, and pre- and post-course surveys. The personnel effort associated with the production and delivery of the three MOOCs are summarized in Table 5, based on time use as logged by the AMNH project manager. The project manager and project director spent the equivalent of 25 and 11 entire workweeks respectively on the project, while the instructors spent, on average, about six workweeks each, shooting videos and developing, adapting, or reviewing course content. The core team met once or twice per week for one to two hours to plan, design, execute, and review the MOOC production and delivery. A TA managed the discussion forums, processed survey responses, and reviewed the platform data.

Using national average salaries and benefits rates for personnel, wherever possible at similar positions in postsecondary institutions to allow comparability with the other MOOC costs we present, we estimate the personnel costs to develop the three MOOCs created by AMNH at $78,470 per MOOC and total costs at $104,620 per MOOC. Of the total 39,685 participants who initially enrolled in the three MOOCs, 1,155 completed and passed all course requirements. Costs per completer for the MOOCs amount to $272.

Time-by-task and cost analysis for Big Data in Education development and delivery.

Big Data in Education was an eight-week MOOC delivered on the Coursera platform in late 2013. Ryan Baker, a faculty member at Teachers College, Columbia University, developed the course by adapting a 16-week on-campus version usually taught to classes ranging in size from eight to fifteen students. Planning and preparation for the course began in mid-March 2013. Big Data in Education was free, open to any participant, and non-credit-bearing. There were 48,058 registrants and 526 of them completed the last assignment. Baker kept track of time and tasks related to the MOOC in an Excel spreadsheet from June (when our study began) to the end of December 2013. Hours spent on activities prior to June were estimated. Total time logged plus time estimated was 176 hours, with the heaviest burden falling during the first three months of planning and preparation of materials, the month prior to launch, and the first few weeks of course delivery. Time spent on various tasks included: creating course materials such as slides, assignments, and quizzes (58 hours); set-up and video-recording using ScreenFlow software (46 hours yielding 6 1/2 hours of finished video used in the MOOC); planning, bureaucracy, and coordination with Coursera, the TA, and the course production team (37 hours); participating in the forums and responding to participant e-mails (26 hours); "debugging" slides, assignments, and quiz questions during the course (7 hours); and open office hours (3 hours).

In addition to Baker, several other personnel worked on the MOOC. A TA spent approximately 15 hours per week over 16 weeks for a total of 240 hours. Tasks included coordinating among faculty member, video team, and Coursera's course coordinator;

checking that uploaded videos were working; posting assignments and "inline" quiz questions (which are embedded in the videos); and participating in the discussion forum. Seven individuals from the Educational Data Mining Laboratory at Teachers College read and participated in the discussion forums. We estimate two hours per person per week over the eight-week period for a total of 112 hours. A senior administrator coordinated the production activities one hour per week for eight weeks. Two in-house video-specialists edited the video, linked files, requested captioning, and uploaded video for 32 hours. A senior educational technologist served as the day-to-day project manager for MOOC production and delivery for a total of 75 hours. This included monitoring the online discussion forum for technical questions.

We estimated personnel costs of $29,240 (see Table 6) to replicate the development and delivery of Big Data in Education using national average salaries and benefit rates for postsecondary personnel at private universities, and total costs of $38,980. With 526 students completing Big Data in Education, estimated costs per completer are $74.

Table 6

Personnel Costs for Big Data in Education Development and Delivery

Personnel ingredients	Cost
Faculty member	$12,354
Teaching assistant	$4,950
Forum monitors	$5,377
Education administrator - educational support services	$584
Educational technologist: project manager	$4,725
Video editor	$1,248
Total personnel costs	$29,238

Sources: Ryan Baker and Yuan "Elle" Wang, Teachers College, Columbia University; Michael Cennamo, CCNMTL, Columbia University.

Discussion and Conclusions

Overall, we found that costs of developing and delivering MOOCs at the four institutions varied widely, ranging from $38,980 to $325,330 per MOOC. Based on our limited sample of eight MOOCs, the key variables in determining costs do not appear to include course length or whether the course is designed as a cMOOC or as an xMOOC. Costs depend heavily on the number of people involved in the MOOC production process and to what extent it is executed "in-house" as opposed to by external professionals. Additionally, platform programming costs to facilitate the extensive auto-grading or peer-grading functionalities necessary to accommodate the huge enrollments, or to provide simulated lab experiences can be high. Course design and delivery has shifted from a solo endeavor to a team effort, often including administrators in offices of digital technology, instructional designers, instructional technologists, videographers, and project managers. While involvement of multiple professionals is typical of what Bates (2005) describes as the "project management" model for web-based course development, the higher visibility of MOOCs, and the objective of building or enhancing brand appears to have led institutions to dedicate more resources for the planning and production of MOOCs compared with regular online courses, often including senior level administrators and external video producers who provide very high production values. Faculty members are generally undercompensated for the opportunity costs of their time to develop MOOC content.

Cost Comparison: MOOCs, Online, and Hybrid learning

We did not find pre-existing estimates of MOOC production and delivery costs derived from records of personnel effort with which to compare our findings. The E-Learning Working Group at the University of Ottawa estimated costs of developing a Coursera MOOC at C$110,000 and costs of delivery at C$29,000, for a total of C$139,000 (Boddy et al., 2013). The U.S. dollar equivalent of $127,500 falls within the range of our own estimates. To provide another point of comparison for our results, we replicated the projected costs for Georgia Institute of Technology's Online M.S. in Computer Science program (see GTRC/Udacity, 2013), added a conservative estimate of costs for the head TAs/course developers which appear to have been omitted, and calculated an average cost per course of $226,000-$284,000, including both new courses and re-runs. While at the high end of our range of cost estimates, these courses provide significantly more student support and ongoing instructor involvement.

Limited publicly available information exists on the institutional costs of contemporary postsecondary online courses against which we can compare the costs of MOOCs. Bates provides a useful benchmark estimating costs of $35,000-$50,000 to develop a regular three-credit online course delivered on a learning management system. He notes that, within the context of a program, these costs constitute less than 20% of the total, once costs of delivery, including student support and assessment, are included (A. Bates, personal communications, April 29, 2014, May 15, 2014; Bates & Sangra, 2011). Conversely, we estimated that for Big Data in Education the delivery costs constituted only 20%-30% of the total cost, with production costs accounting for the majority. Using Bates' guideline, total costs per regular online course for both development and delivery would amount to $175,000-$250,000, at the higher end of the range we found for total MOOC costs.

Ithaka S+R (2014) attempted to estimate costs of hybrid courses developed and delivered at the University System of Maryland. The report indicates that 12 faculty members spent between 40 and 506 hours to plan their hybrid courses, some of which incorporated MOOCs or MOOC components, plus another four hours per week on delivery. If we assume 16-week courses and national average salary and benefits rates for average faculty at public universities, the faculty costs amount to between $6,500 and $36,000. These numbers fall within the range of our estimates of faculty costs for MOOC production and delivery.

One metric for assessing cost-effectiveness of MOOCs relative to regular online courses is institutional cost per student completing the course. In our study we were able to estimate this metric in the cases where completion data were available. Cost per completer for Big Data in Education was $74 and the average cost per completer across the three AMNH MOOCs was $272. By comparison, if we use Bates' cost estimates for regular online courses and spread the total course costs over a typical online class size of 30 students, cost per completer would be much higher: assuming a completion rate of 82% for online courses (based on Xu & Jaggars, 2011) cost per completer would be $7,000-$10,000. In practice, cost per completer would be lower if the course is offered multiple times, but this is true for both the regular courses and for the MOOC. At a cost of $175,000, the number of students completing a regular online course would need to reach over 2,300 to be as cost-effective for completion as Big Data in Education.

It therefore appears that while MOOC production is often more costly than the development of regular online courses, the ability to scale MOOCs and the absence of associated student supports results in a dramatically lower cost per completer. Considering that MOOCs can help achieve other objectives not generally addressed by regular online courses, including branding, global reach, and large scale research, MOOCs would appear to be a wise use of resources, if only the costs could be recovered through tuition or other fees.

However, it is arguable that course completion per se is not a satisfactory measure of effectiveness and that MOOCs should be judged on the quality and quantity of learning that takes place. To date, almost no peer-reviewed studies have been published comparing pedagogical effectiveness of MOOCs with alternative delivery modes. One exception is Colvin et al. (2014) who rigorously document absolute and relative learning in a physics MOOC using pre- and post-testing and item response theory, and compare the results with on-campus instruction. Colvin et al. find that participants in the MOOC showed learning gains slightly higher than for students in a traditional on-campus course, but lower than for students in courses that rely on interactive engagement pedagogy. As no cost estimates are available in this study, it is not possible to assess cost-effectiveness of the MOOC except to note that, given apparently similar learning gains, even if the MOOC is more expensive to produce than the on-campus course, its ability to serve many more students will likely render it more cost-effective. One important caveat is that, with few instructor-student interactions and student supports, MOOCs are likely completed only by self-sufficient, motivated students. It is possible that MOOCs are cost-effective for this subset of learners, but not for less motivated learners.

Sustainability of MOOCs

We found that the costs of re-running Connectivism and Connected Knowledge were around 38% lower than the costs of the initial offering. Given the intense level of instructor involvement in cMOOCs, this is unlikely to be a useful predictor for xMOOC re-runs where instructor involvement may be minimal or absent. One interviewee at a community college expected that the re-run costs for the college's xMOOC would be small, perhaps less than $1,000, compared with her estimate of $75,000 for the initial offering. Such assumptions should be rigorously tested through careful cost analyses and we recommend that, going forward, MOOC producers attempt to document these re-run costs to help assess the sustainability of MOOC production.

Given the highly labor-intensive nature of the process, we do not expect the costs of new MOOC production to fall significantly over time. While it appears that revenue streams for MOOCs are slowly building, we expect that unless MOOC producers can offer credentials of economic value in order to attract fee-paying participants, or can use MOOCs to replace traditional offerings more efficiently, most likely by reducing expensive personnel, they will not be able to afford ongoing participation in the current MOOC experimentation. Free, non-credit bearing MOOCs are likely to remain available only from the wealthiest institutions that can subsidize the costs from other sources of funds.

Future Directions

Several questions remain to be explored with respect to MOOC costs and cost-effectiveness and whether they can eventually contribute to reducing the costs of higher education. Cost analyses of MOOC re-runs would help ascertain whether costs of re-offering a MOOC diminish substantially as compared with the initial offering. We recommend that future analyses of MOOC costs aim to estimate actual costs of materials, equipment, facilities, and overhead as opposed to simply assuming, as we did, that these items account for 25% of total costs. Jones (2004), Bates (2005), and Rumble (1997), while acknowledging the difficulty of estimating overhead costs for technology-mediated distance instruction, offer valuable guidelines for this endeavor. The feasibility of sharing courses across multiple campuses must be explored, as should the question of whether, over the longer term, variable costs of MOOCs can be contained by automating functions and substituting instructional support provided by expensive faculty members with less costly TAs, part-time instructors, or peer-to-peer learning and assessment.

Studies of MOOC effectiveness with respect to educational outcomes should be combined with cost analyses to help determine whether spending more on MOOC production and delivery leads to better learning outcomes. For example, does higher quality video production lead to higher rates of course completion or greater acquisition and retention of knowledge? Does substituting tenured faculty members with non-tenured instructors or TA's affect student performance and learning in MOOCs? While it is difficult to set up true experiments in higher education (Bowen, Chingos, Lack, & Nygren, 2012), it may be possible to address some of these questions by conducting side-by-side comparisons similar to those Ithaka S+R (2014) executed at the University System of Maryland.

To answer the question of whether MOOCs are a cost-effective means to deliver education, we must be able to compare the costs of MOOCs to the costs of alternative delivery mechanisms, as well as the effectiveness of each alternative with respect to a common outcome of interest, such as increasing participants' level of knowledge or skill in a specific subject area. Generating cost-effectiveness ratios for a number of educational alternatives including MOOCs would allow decision-makers to choose which programs represent the best investments of resources. Longitudinal studies tracking post-MOOC outcomes such as sequences of courses taken, professional certifications obtained, or job opportunities received would help assess the longer term economic value of participating in these courses and allow for cost-benefit analyses to estimate the overall returns to society of investing in MOOC creation.

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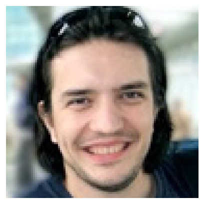
Where is Research on Massive Open Online Courses Headed? A Data Analysis of the MOOC Research Initiative

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Abstract

This paper reports on the results of an analysis of the research proposals submitted to the MOOC Research Initiative (MRI) funded by the Gates Foundation and administered by Athabasca University. The goal of MRI was to mobilize researchers to engage into critical interrogation of MOOCs. The submissions – 266 in Phase 1, out of which 78 was recommended for resubmission in the extended form in Phase 2, and finally, 28 funded – were analyzed by applying conventional and automated content analysis methods as well as citation network analysis methods. The results revealed the main research themes that could form a framework of the future MOOC research: i) student engagement and learning success, ii) MOOC design and curriculum, iii) self-regulated learning and social learning, iv) social network analysis and networked learning, and v) motivation, attitude and success criteria. The theme of social learning received the greatest interest and had the highest success in attracting funding. The submissions that planned on using learning analytics methods were more successful. The use of mixed methods was by far the most popular. Design-based research methods were also suggested commonly, but the questions about their applicability arose regarding the feasibility to perform multiple iterations in the MOOC context and rather a limited focus on technological support for interventions. The submissions were dominated by the researchers from the field of education (75% of the accepted proposals). Not only was this a possible cause of a complete lack of success of the educational technology innovation theme, but it could be a worrying sign of the fragmentation in the research community and the need to increased efforts towards enhancing interdisciplinarity.

Keywords: Massive online open courses; MOOC; content analysis; MOOC research analysis; MOOC Research Initiative; education research

Introduction

Massive open online courses (MOOCs) have captured the interest and attention of academics and the public since fall of 2011 (Pappano, 2012). The narrative driving interest in MOOCs, and more broadly calls for change in higher education, is focused on the promise of large systemic change. The narrative of change is some variant of:

> Higher education today faces a range of challenges, including reduced public support in many regions, questions about its role in society, fragmentation of the functions of the university, and concerns about long term costs and system sustainability.

In countries like the UK and Australia, broad reforms have been enacted that will alter post-secondary education dramatically (Cribb & Gewirtz, 2013; Maslen, 2014). In the USA, interest from venture capital raises the prospect of greater privatization of universities (GSV Advisors, 2012). In addition to economic questions around the sustainability of higher education, broader socio-demographic factors also influence the future of higher education and the changing diversity of the student population (OECD Publishing, 2013).

Distance education and online learning have been clearly demonstrated to be an effective option to traditional classroom learning[1]. To date, online learning has largely been the domain of open universities, separate state and provincial university departments, and for-profit universities. Since the first offering of MOOCs and by elite universities in the US and the subsequent development of providers edX and Coursera, online learning has now become a topical discussion across many campuses[2]. For change advocates, online learning in the current form of MOOCs has been hailed as transformative, disruption, and a game changer (Leckart, 2012). This paper is an exploration of MOOCs; what they are, how they are reflected in literature, who is doing research, the types of research being undertaken, and finally, why the hype of MOOCs has not yet been reflected in a meaningful way on campuses around the world. With a clear foundation of what the type of research actually happening in MOOCs, based on submissions to the MOOC Research Initiative[3], we are confident that the conversation about how MOOCs and online learning will impact existing higher education can be moved from a hype and hope argument to one that is more empirical and research focused.

1 http://nosignificantdifference.org

2 In this paper, we consider MOOCs to belong to the broader field of online education and learning and that their research should be built on and expand the existing body of research knowledge of online education and learning.

3 http://www.moocresearch.com

Massive Online Open Courses (MOOCs)

Massive open online courses (MOOCs) have gained media attention globally since the Stanford MOOC first launched in fall of 2011. The public conversation following this MOOC was unusual for the education field where innovations in teaching and learning are often presented in university press releases or academic journals. MOOCs were prominent in the *NY Times*, *NPR*, *Time*, *ABC News*, and numerous public media sources. Proclamations abounded as to the dramatic and significant impact that MOOCs would have on the future of higher education. In early 2014, the narrative has become more nuanced and researchers and university leaders have begun to explore how digital learning influences on campus learning (Kovanović, Joksimović, Gašević, Siemens, & Hatala, 2014; Selwyn & Bulfin, 2014). While interest in MOOCs appears to be waning from public discourse, interest in online learning continues to increase (Allen & Seaman, 2013). Research communities have also formed around learning at scale[4] suggesting that while the public conversation around MOOCs may be fading, the research community continues to apply lessons learned from MOOCs to educational settings.

MOOCs, in contrast to existing online education which has remained the domain of open universities, for-profit providers, and separate departments of state universities, have been broadly adopted by established academics at top tier universities. As such, there are potential insights to be gained into the trajectory of online learning in general by assessing the citation networks, academic disciplines, and focal points of research into existing MOOCs. Our research addresses how universities are approaching MOOCs (departments, research methods, and goals of offering MOOCs). The results that we share in this article provide insight into how the gap between existing distance and online learning research, dating back several decades, and MOOCs and learning at scale research, can be addressed as large numbers of faculty start experimenting in online environments.

MOOC Research

Much of the early research into MOOCs has been in the form of institutional reports by early MOOC projects, which offered many useful insights, but did not have the rigor – methodological and/or theoretical expected for peer-reviewed publication in online learning and education (Belanger & Thornton, 2013; McAuley, Stewart, Siemens, & Cormier, 2010). Recently, some peer reviewed articles have explored the experience of learners (Breslow et al., 2013; Kizilcec, Piech, & Schneider, 2013; Liyanagunawardena, Adams, & Williams, 2013). In order to gain an indication of the direction of MOOC research and representativeness of higher education as a whole, we explored a range of articles and sources. We settled on using the MOOC Research Initiative as our dataset.

4 http://learningatscale.acm.org

MOOC Research Initiative (MRI)

The MOOC Research Initiative was an $835,000 grant funded by the Bill & Melinda Gates Foundation and administered by Athabasca University. The primary goal of the initiative was to increase the availability and rigor of research around MOOCs. Specific topic areas that the MRI initiative targeted included: i) student experiences and outcomes; ii) cost, performance metrics and learner analytics; iii) MOOCs: policy and systemic impact; and iv) alternative MOOC formats. Grants in the range of $10,000 to $25,000 were offered. An open call was announced in June 2013. The call for submissions ran in two phases: 1. short overviews of 2 pages of proposed research including significant citations; 2. full research submissions, 8 pages with influential citations, invited from the first phase. All submissions were peer reviewed and managed in Easy Chair. The timeline for the grants, once awarded, was intentionally short in order to quickly share MOOC research. MRI was not structured to provide a full research cycle as this process runs multiple years. Instead, researchers were selected who had an existing dataset that required resources for proper analysis.

Phase one resulted in 266 submissions. Phase two resulted in 78 submissions. A total of 28 grants were funded. The content of the proposals and the citations included in each of the phases were the data source for the research activities detailed below.

Research Objectives

In this paper, we report the findings of an exploratory study in which we investigated (a) the themes in the MOOC research emerging in the MRI proposals; (b) research methods commonly proposed for use in the proposals submitted to the MRI initiative, (c) demographics (educational background and geographic location) characteristics of the authors who participated in the MRI initiative; (d) most influential authors and references cited in the proposals submitted in the MRI initiative; and (e) the factors that were associated with the success of proposals to be accepted for funding in the MRI initiative.

Methods

In order to address the research objectives defined in the previous section, we adopted the content analysis and citation network analysis research methods. In the remainder of this section we describe both of these methods.

Content Analysis

To address research objectives a and b, we performed content analysis methods. Specifically, we performed both automated a) and manual b) content analyses. The choice of content analysis was due to the fact that it provides a scientifically sound method for conducting an objective and systematic literature review, thus enabling for the generalizability of the conclusions (Holsti, 1969). Both variations of the method have been used for analysis of large amounts of textual content (e.g., literature) in educational research.

Automated content analysis of research themes and trends.

Given that content analysis is a very costly and labor intensive endeavor, the automation of content analysis has been suggested by many authors and this is primarily achieved through the use of scientometric methods (Brent, 1984; Cheng et al., 2014; Hoonlor, Szymanski, & Zaki, 2013; Kinshuk, Huang, Sampson, & Chen, 2013; Li, 2010; Sari, Suharjito, & Widodo, 2012). Automated content analysis assumes the application of the computational methods – grounded in natural language processing and text mining – to identify key topics and themes in a specific textual corpus (e.g., set of documents, research papers, or proposals) of relevance for the study. The use of this method is especially valuable in cases where the trends of a large corpus need to be analyzed in "real-time", that is, short period of time, which was the case of the study reported in this paper and specifically research objective c. Not only is the use of these automated content analysis methods cost-effective, but it also lessens the threats to validity and issues of subjectivity that are typically associated with the studies based on content analysis. Among different techniques, the one based on the word co-occurrence – that is, words that occur together within the same body of written text, such as research papers, abstracts, titles or parts of papers – has been gaining the widespread adoption in the recent literature reviews of educational research (Chang, Chang, & Tseng, 2010; Cheng et al., 2014). As such, the use of automated content analysis was selected for addressing research objective c.

In order to perform a content analysis of the MRI submissions, we used particular techniques adopted from the disciplines of machine learning and text mining. Specifically, we based our analysis approach on the work of Chang et al. (2010) and Cheng et al. (2014). Generally speaking, our content analysis consisted of the three main phases:

1. extraction of relevant *key concepts* from each submission,
2. *clustering* submissions to the important research themes, and
3. *in-depth analysis* of the produced clusters.

For extraction of key concepts from each submission, we selected Alchemy, a platform for semantic analyses of text that allows for extraction of the informative and relevant set of concepts of importance for addressing research objective c, as outlined in Table 1. In addition to the list of relevant concepts for each submission, Alchemy API produced the associated relevance coefficient indicating the importance of each concept for a given submission. This allowed us to rank the concepts and select the top 50 ranked concepts for consideration in the study. In the rare cases when Alchemy API extracted less than 50 concepts, we used all of the provided concepts.

After the concept extraction, we used the agglomerative hierarchical clustering in order to define N groups of similar submissions that represent the N important research themes and trends in MOOC research, as aimed in research objective c. Before running the particular clustering algorithm we needed to: i) define a representation of each submission, ii) provide a similarity measure that is used to define submission clusters, and iii) choose appropriate number of clusters N. As we based the clustering on the extracted keywords using Alchemy API, our representation of each submission was a vector of concepts that appeared in a particular submission. More precisely, we created a large submission-concept matrix where each row represented one submission, and each column represented one concept, while the values in the matrix (MIJ) represented the relevance of a particular concept J for a document I. Thus, each submission was represented as an N-dimensional row vector consisting of numbers between 0.00 and 1.00 describing how relevant each of the concepts was for a particular submission. The concepts that did not appear in the particular submission had a relevance zero, while the concepts that were actually present in the submission text had a relevance value greater than zero and smaller or equal to one.

With respect to the similarity measure, we used the popular cosine similarity which is essentially a cosine of the angle θ between the two submissions in the N-dimensional space defined by all unique concepts. It is calculated as dot product of two vectors divided by the products of their ℓ2 norms. For two submissions A and B, and with the total of n different concepts (i.e., the length of vectors A and B was n – the number of concepts extracted from A and B), it is calculated as follows:

$$similarity(A,B)=\cos(\theta)=\frac{A\times B}{\|A\|\times\|B\|}=\frac{\sum_{i=1}^{n}A_i\times B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2}\times\sqrt{\sum_{i=1}^{n}(B_i)^2}}$$

Agglomerative hierarchical clustering algorithms work by iteratively merging smaller clusters until all the documents are merged into a single big cluster. Initially, each document is in a separate cluster, and based on the provided similarity measure the most similar pairs of clusters are merged into one bigger cluster. However, given that the similarity measure is defined in terms of two documents, and that clusters typically consist of more than one document, there are several strategies of measuring the similarity of clusters based on the similarity of the individual documents within clusters. We used the GAAClusterer (i.e., Group Average Agglomerative) hierarchical clustering algorithm from the NLTK python library that calculates the similarity between each pair of clusters by averaging across the similarities of all pairs of documents from two clusters.

Table 1

Concept Categories for Describing Clusters

Category	Description	Example
Topics	The most frequent keywords that identify topics mentioned in the specific cluster.	Intelligent tutoring systems; Educational technology; Networked contexts
Theory/ Approach	Keywords that identify specific theory recognized within documents in each cluster.	Competence-based education; Social constructivist method
Environment	MOOC platform identified within the cluster.	Coursera; edX; MiriadaX
Domain	Keywords that represent a specific domain of a MOOC course.	STEM disciplines; Red Cross; Health Sciences
Data sources	Keywords representing data used for studies within the cluster.	Engagement data; Qualitative data; Study logs
Measures and variables	Keywords representing measures used for studies within the cluster.	Student outcome measures; Early motivation measures;
Analysis techniques	Keywords representing various analysis used for studies within the cluster.	Parallel multi-method analysis; Nonparametric statistical analysis;
Research instruments	Keywords representing various instruments used to collect data for studies within the cluster.	In-depth interviews; Focus group interview; Questionnaire
Use of control group	Identifies whether Control groups are used in at least one study within the cluster.	Control group

The output of the clustering algorithm was a tree, which described the complete clustering process. We evaluated manually the produced clustering tree to select the clustering solution with the N most meaningful clusters for our concrete problem. In the phase one of the MRI granting process we discovered nine clusters, while in the second phase we discovered five clusters.

Finally, in order to assess the produced clusters and select the key concepts in each cluster, we created a concept-graph consisting of the important concepts from each cluster. The nodes in a graph were concepts discovered in a particular cluster, while the links between them were made based on the co-occurrence of the concepts within the same document. More precisely, the undirected link between two concepts was created in case that both of them were extracted from the same document. To evaluate the relative importance of each concept we used the betweenness centrality measure, as the key concepts are likely the ones with the highest betweenness centrality. Besides the ranking of the concepts in each cluster based on their betweenness centrality, we manually classified all important concepts into one of the several categories that are shown in Table 1. Provided categories represent important dimensions of analysis and we describe each of the clusters based on the provided categories of key concepts. Thus, when we describe a particular cluster, we cover all of the important dimensions to provide the holistic view of the particular research trend that is captured in that cluster.

Content analysis of important characteristics of authors and submissions.

A manual content analysis of the research proposals was performed in order to address research objective b. The content analysis afforded for a systematic approach to collect data about the research methods and the background of the authors. These data are then used to cross-tabulate with the research themes found in the automated content analysis (i.e., research objective a) and citation analysis (i.e., research objective c). Specifically, each submission was categorized into one of the four categories in relation to research objective a:

1. *qualitative method*, which meant that the proposal used a qualitative research method such as grounded theory;

2. *quantitative method*, which meant that a proposal followed some of the quantitative research methods on data collected through (Likert-scale based) surveys or digital traces recorded by learning platforms in order to explore different phenomena or test hypotheses;

3. *mixed-methods*, which reflected a research proposals that applied some combination of qualitative and quantitative research methods;

4. *other*, which comprised of the research proposals that did not explicitly follow any of these methods, or it was not possible to determine from their content which of the three methods they planned to use.

For all the authors[5] of submitted proposals to the MRI initiative, we collected the information related to their home discipline and the geographic location associated with their affiliation identified in their proposal submissions in order to address research objective c. Insight into researchers' home discipline was obtained from the information provided with a submission (e.g., if a researcher indicated to be affiliated with a school

[5] Information about the geographic location as extracted from the application forms submitted by the authors to EasyChair, a software system used for the submission and review process.

of education, we assigned education as the home discipline for this research). In cases when such information was not available directly with the proposal submission, we performed a web search, explored institutional websites, and consulted social networking sites such as LinkedIn or Google Scholar.

Citation Analysis and Success Factors

The citation analysis was performed to address research objective d. It entailed the investigation of the research impact of the authors and papers cited in the proposals submitted to the MRI initiative (Waltman, van Eck, & Wouters, 2013). In doing so, the counts of citations of each reference and author, cited in the MRI proposals, are used as the measures of the impact in the citation analysis. This method was suitable, as it allowed for assessing the influential authors and publications in the space of MOOC research.

Citation network analysis – the analysis of s0-called co-authorship and citation networks have gained much adoption lately (Tight, 2008) – was performed in order to assess the success factor of individual proposals to be accepted for funding in the MRI initiative, as set in research objective e. This way of gauging the success was a proxy measure of the quality and importance of the proposals, as aimed in research objective e. As such, it was appropriate to be used as an indicator of specific topics based on the assessment of the international board of experts who reviewed the submitted proposals.

Social network analysis was used to address research objective e. In this study, social networks were created through the links established based on the citation and co-authoring relationships, as explained below. The use of social network analysis has been shown as an effective way to analyze professional performance, innovation, and creativity. Actors occupying central networks nodes are typically associated with the higher degree of success, innovation, and creative potential (Burt, Kilduff, & Tasselli, 2013; Dawson, Tan, & McWilliam, 2011). Moreover, structure of social networks has been found as an important factor of innovation and behavior diffusion. For example, Centola (2010) showed that the spread of behavior was more effective in networks with higher clustering and larger diameters. Therefore, for research objective e, we expected to see the association between the larger network diameter and the success in receiving funding.

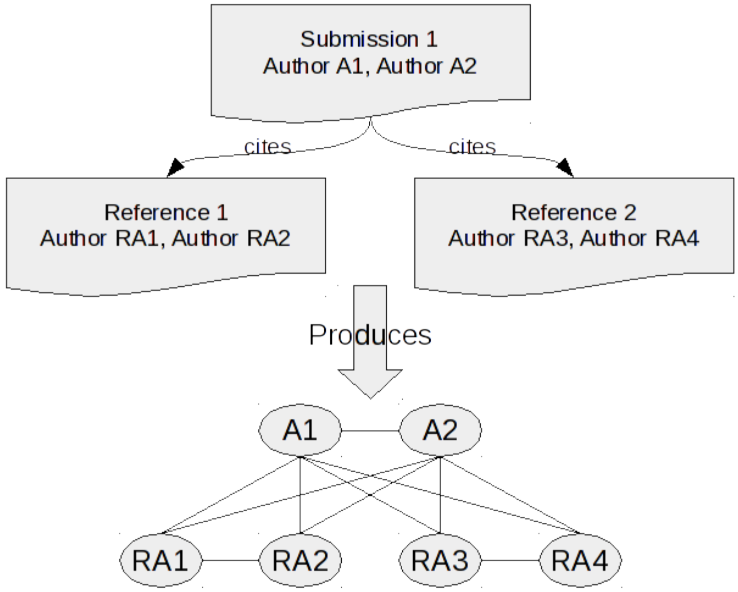

Figure 1. The citation networks – connecting the authors of a research proposal (A1 and A2) with the authors of two cited references (RA1, RA2, RA2 and RA4).

In this study, we followed a method for citation network analysis suggested by Dawson et al. (2014) in their citation network analysis of the field of learning analytics. Nodes in the network represent the authors of both submissions and cited references, while links are created based on the co-authorship and citing relations. Figure 1 illustrates the rules for creating the citation networks in the simple case when a submission written by the two authors references two sources, each of them with two authors as well.

We created a citation network for each cluster separately and analyzed them by the following three measures commonly used in social network analysis (Bastian, Heymann, & Jacomy, 2009; Freeman, 1978; Wasserman, 1994):

1. *degree*, the number of edges a node has in a network,
2. *diameter*, the maximum eccentricity of any node in a network, and
3. *path*, the average graph-distance between all pairs of nodes in a network.

All social networking measures were computed using the Gephi open source software for social network analysis (Bastian et al., 2009). The social networking measures of each cluster were then correlated (Spearman's ρ) with the acceptance ratio – computed as a ratio of the number of accepted proposals and the number of submitted proposals – for both phases of the MRI initiative.

Results

Phase 1 Results

Phase 1 research themes.

In order to evaluate the direction of the MOOC related research, we looked at the most important research themes in the submitted proposals. Table 2 shows the detailed descriptions of the discovered research themes and their acceptance rates, primary research fields of authors, as well as the average number of authors and citations on each submission. In total, there were nine research themes with a similar number of submissions, from 19 (i.e., "Mooc Platforms" research theme) to 40 (i.e., "Communities" and "Social Networks" research themes). Likewise, submissions from all themes had on average slightly more than 2 authors and from 7 to 9 citations. However, in terms of their acceptance rates, we can see much bigger differences. More than half of the papers from the "Social Networks" research theme moved to the second phase and finally 25% of them were accepted for funding, while none of the submissions from the "Education Technology Improvements" theme was accepted for funding.

Furthermore, Table 3 shows the main topics and research approaches used in each research theme, while Table 4 shows the most important methodological characteristics of each research theme.

Table 2

Phase 1 Research Themes

Theme	Size	Accepted 2nd round	Accepted funding	Authors avg. (SD)	Citations avg. (SD)	Major fields
Cluster 1 Ed. Tech. Improvements	23	4 (17.4 %)	0 (0 %)	2.7 (1.1)	7.3 (3.6)	Education (36) Business (8)
Cluster 2 Processes	26	10 (38.5 %)	2 (7.7 %)	2.6 (1.7)	6.2 (2.8)	Education (38) Computer Science (8)
Cluster 3 High Ed. Institutions and MOOCs	25	5 (20.0 %)	1 (4.0 %)	2.1 (1.1)	9.0 (5.5)	Education(16) Social Sciences (9)
Cluster 4 Motivation and Behavioral Patterns	29	13 (44.8 %)	4 (13.8 %)	2.1 (0.9)	6.9 (4.6)	Education (29) Computer Science (8)
Cluster 5 Mobile and Adaptive Learning	35	8 (22.9 %)	4 (11.4 %)	2.2 (1.2)	8.3 (6.3)	Education (27) Computer Science (8)
Cluster 6 Learner Performance	24	5 (20.8 %)	2 (8.3 %)	2.4 (1.5)	8.3 (6.6)	Education (18) Industry (10)
Cluster 7 MOOC Platforms	19	2 (10.5 %)	1 (5.3 %)	2.2 (1.1)	9.1 (7.0)	Education (13) Technology (6) Industry (6)
Cluster 8 Communities	40	9 (22.5 %)	4 (10.0 %)	2.3 (1.2)	6.8 (4.8)	Education (42) Industry (15)
Cluster 9 Social Networks	40	22 (55.0 %)	10 (25.0 %)	2.2 (1.2)	8.3 (5.9)	Education (34) Computer Science (15)
Total	261	78 (29.9 %)	28 (10.7 %)			

Table 3

Phase 1 Research Themes Topics and Theoretical Approaches

Theme	Topics	Theoretical approaches
Cluster 1 Ed. Tech. Improvements	Intelligent tutoring systems Educational technology Networked contexts Deeper learning experience	Behavioral leadership theory Grounded theory Data-driven approach Design-based research Rapid prototyping approach
Cluster 2 Processes	Teaching-learning process Intellectual property issues Collaborative learning Forum discussion Social learning approach Self-regulated learning Learner engagement	Connectivist approach Descriptive research study Mixed method approach Thematic analysis Semiotic social theory Agile development models Longitudinal research
Cluster 3 High Ed. Institutions and MOOCs	Student perception Student achievement Highly-motivated students Higher education Online social worlds Collaborative activity	Competence-based education Social constructivist method Cognitive-behaviorist approach Innovation diffusion theory Ethnographic approach Flipped classroom style class
Cluster 4 Motivation and Behavioral Patterns	Student engagement Discussion forum entries Student motivation Student behavioral patterns Social media Blended learning courses Retention analysis	Exploratory study Cognitive science research Field research methods Flipped classroom model Problem based learning Theory of planned behavior
Cluster 5 Mobile and Adaptive Learning	Collaboration Mobile learning Content drop-out pattern Social networking Emergent learning Personal learning env. Learner engagement	Social learning theory Thematically based approach Social psychology Action research MSLQ cognitive strategy phenomenological study Flipped classroom concept
Cluster 6 Learner Performance	Personality data Educational technology Student demographics Course completion Student performance Gamification techniques	Flipped Classroom model Problem-based learning
Cluster 7 MOOC Platforms	Traditional education Instructional design Higher education practice xMOOC model	Problem-based learning Blended learning approach Psychometric theory Design-based research
Cluster 8 Communities	Online communities Discussion forums Completion rates Educational technology Self-directed learning	Ethnographic approach Mixed methods Design-based research approach Evidence-Based Learning Networked Learning Framework

	Formal-learning environment Technology-enhanced learning Innovative business models Better retention	Behaviourism theory Connectivist theory
Cluster 9 Social Networks	Social network analysis Peer-to-peer interaction Peer assessment Student success Higher education Peer tutoring Discussion Forums Social learning Student motivation	Interdisciplinary approach Phenomenological study Design Based Research Flipped classroom Game theory simulation Actor network theory

Table 4

Phase 1 Research Themes Data Analysis Characteristics

Theme	Data sources and measures	Analysis techniques	Instruments
Cluster 1 Ed. Tech. Improvements	Engagement data Study logs Activity logs Feedback data Student success measures	Post-test implementation surveys Data classification Association rule mining Granular taxonomy Big data analytics	In-depth interviews Focus group interviews Online surveys
Cluster 2 Processes	Conversational data Narrative data Clickstream data Linguistic data Formative evaluation data Open research data	Cross-case analysis Critical literature survey Interactive language analysis Discourse analysis	Self-assessment instruments Focus groups Instructor survey Student surveys
Cluster 3 High Ed. Institutions and MOOCs	Social Media Rich qualitative data MOOC-related data Descriptive data Field data Post-instruction outcome measures	Meta-analysis method Focused content analysis Comparative analysis Meta-narrative analysis	Focus groups Interviews Survey instruments Questionnaires Participant observation Field notes
Cluster 4 Motivation and Behavioral Patterns	International mobility statistics Web traffic statistics Performance data Tracking log data Behavioral data Observational data Clickstream data Student outcome	Graph analysis Deep linguistic analyses Behavioral analysis Structural analysis Natural language processing Time series analysis	Interviews Student surveys Quizzes

	measures Early motivation measures		
Cluster 5 Mobile and Adaptive Learning	Activity log data Discursive data Email tracking data Social graph data Client-side offline data Social psychological measures	Online ethnography Trace analysis	Surveys Questionnaires Participant observations Phenomenological inquiry
Cluster 6 Learner Performance	Student survey data Clickstream data Student performance data Learner data Activity logs	Latent Dirichlet analysis Comparative analysis Clickstream analytics Learner analytics Comparative analytics	Memorization tests Interviews Surveys Focus groups Feedback questionnaires
Cluster 7 MOOC Platforms	Log data	Performance data analysis Content analysis	Surveys Interviews Self-assessments Performance assessment Summative assessment
Cluster 8 Communities	Interview transcripts Online artifacts Assessment data	In-depth analysis Text Analysis Systematic discourse analysis Frame analysis Critical analysis	Focus groups Surveys Semi-structured interviews
Cluster 9 Social Networks	Learner interaction data Phenomenological data EEG-MOOC usage data Course completion data Engagement measures	Cross-case analysis Phenomenological analysis Evidence-based research Content analysis	Exit surveys Qualitative surveys Phenomenological interviews Phenomenological inquiry Interviews End-of-course surveys

Table 5

Phase 1 Distribution of Research Methodologies

Methodology	Submissions	Authors avg. (SD)	Citations avg. (SD)
Mixed	96 (36.2%)	2.4 (1.3)	8.2 (5.0)
Qualitative	74 (27.9%)	2.1 (1.1)	8.6 (6.4)
Quantitative	80 (30.2%)	2.4 (1.3)	6.6 (4.8)
Unknown	15 (5.7%)	1.7 (0.9)	7.1 (5.0)
Total	265 (100.00%)	2.3 (1.2)	7.7 (5.4)

Phase 1 research methods.

Table 5 shows the distribution of submissions per each methodology together with the average number of authors and citations per submission. Although the observed differences are not very large, we can see that the most common research methodology type is mixed research, while the purely qualitative research is the least frequent.

Phase 1 demographic characteristics of the authors.

Table 6 also shows the five most common primary research fields for submission authors. Given that some of the authors were not from academia, we included an additional field entitled "Industry" as a marker for all researchers from the industry field. We can see that researchers from the field of education represent by far the biggest group, followed by the researchers from the industry and computer science fields. Table 7[6] shows a strong presence of the authors of the proposals from North America in Phase 1. They are followed by the authors from Europe and Asia, who combined had a much lower representation than the authors from North America. The authors from other continents had a much smaller presence, with very low participation of the authors from Africa and South America and with no author from Africa who made it to Phase 2.

[6] The numbers of authored and accepted proposals are decimal, as some proposals had authors from different continents. For example, if a proposal had two authors from North America and one author from Africa, the number of authored proposals for North America would be 0.67 and for Africa 0.33.

Table 5

Phase 1 Top 5 Research Fields

Field	Authors
Education	251
Industry	58
Computer Science	58
Social Sciences	32
Engineering	30

Table 6

Phase 1 Geographic Distribution of the Authors

Continent	Authors	Authored proposals	Accepted proposals
Africa	4	3	0
Asia	87	34.38	3.67
Australia/NZ	23	10.33	6
Europe	137	60.51	15.83
North America	305	153.26	54.5
South America	9	4.5	1

Phase 1 citation analysis.

With respect to citation analysis, we extracted the list of most cited authors and papers. We counted an author's – authors of both MIR submissions and the papers cited in the submissions were included – citations as a sum of all of the authors' paper citations, regardless of whether the author was the first author or not. Figure 2 shows the list of most cited authors, while Table 8 shows the list of most cited papers in the first phase of the MRI initiative.

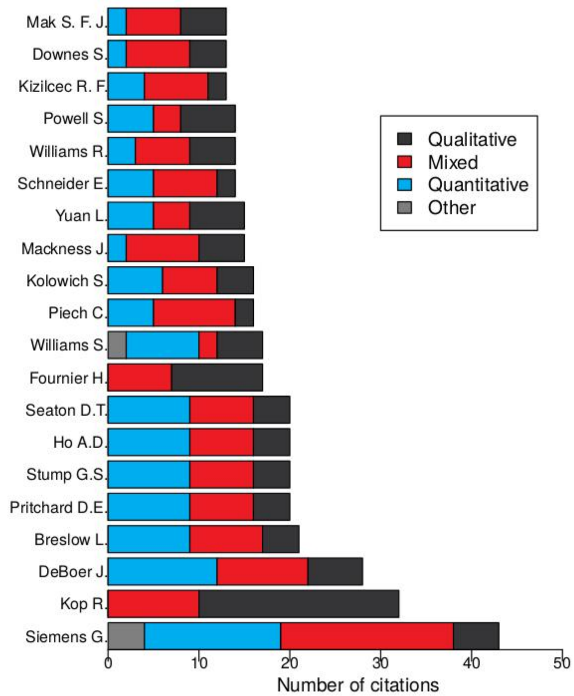

Figure 2. Phase 1 most cited authors.

Table 7

Phase 1 Most Cited papers

Paper name	Citation count
Breslow, L., Pritchard, D.,DeBoer, J., Stump, G., Ho, A. and Seaton, D. (2013). *Studying Learning in the Worldwide Classroom: Research into edX's First MOOC.*	28
Yuan, L. and Powell, S. (2013). *MOOCs and open education: Implications for higher education.*	14
Kizilcec, R. F., Piech, C. and Schneider, E. (2013). *Deconstructing Disengagement: Analyzing Learner Subpopulations in Massive Open Online Courses.*	14
Kop, R., Fournier, H. and Sui Fai Mak, J. (2011). *A pedagogy of abundance or a pedagogy to support human beings? Participant support on Massive Open Online Courses.*	14
Siemens, G. (2005). *Connectivism: A Learning Theory for the Digital Age.*	13
Daniel, J., (2012). *Making sense of MOOCs: Musings in a maze of myth, paradox and possibility.*	13
Mackness, J., Mak, S. and Williams, R. (2010).*The ideals and reality of participating in a MOOC.*	11
Pappano, L. (2012). *The year of the MOOC.*	9

Finally, we extracted for each research theme a citation network from all Phase 1 submissions. Table 9 shows the graph centrality measures for the citation networks of each of the research themes.

Phase 1 success factors.

We looked at the correlations between the centrality measures of citation networks (Table 9) and the second phase acceptance rates. Spearman's rho revealed that there was a statistically significant correlation between the citation network diameter and number of submissions accepted into the second round (ρs= .77, n=9, p<.05), a statistically significant correlation between citation network diameter and second round acceptance rate (ρs= .70, n=9, p<.05), and a statistically significant correlation between citation network path and number of submissions accepted into the second round (ρs= .76, n=9, p<.05). In addition, a marginally significant correlation between citation network path length and second phase acceptance rate was also found (ρs= .68, n=9, p=0.05032). These results confirmed the expectation stated in the citation analysis section that research proposals with the broader scope of the covered literature were more likely to be assessed by the international review board as being of higher quality and importance. Further implications of this result are discussed in the Discussion section.

Table 8

Phase 1 Citation Network Metrics

Theme	Average degree (SD)	Diameter	Average shortest path (SD)	Density
Cluster 1 Ed. Tech. Improvements	4.8 (6.2)	6	3.1 (1.6)	0.018
Cluster 2 Processes	5.4 (5.7)	12	4.6 (2.3)	0.026
Cluster 3 High Ed. Institutions and MOOCs	4.2 (6.3)	8	4.0 (1.5)	0.021
Cluster 4 Motivation and Behavioral Patterns	3.6 (5.6)	9	5.6 (2.3)	0.013
Cluster 5 Mobile and Adaptive Learning	4.8 (7.7)	8	3.8 (1.2)	0.016
Cluster 6 Learner Performance	5.5 (7.1)	7	3.9 (1.8)	0.028
Cluster 7 MOOC Platforms	5.6 (8.9)	8	4.1 (1.9)	0.026
Cluster 8 Communities	5.7 (5.7)	10	4.6 (1.8)	0.023
Cluster 9 Social Networks	4.3 (7.1)	10	5.1 (2.0)	0.01
Total	5.8 (8.7)	17	5.2 (1.5)	0.003

Phase 2 Results

Following the analysis of the first phase of MRI, we analyzed the total of 78 submissions that were accepted into the second round of evaluation.

Phase 2 research themes.

Following the analysis of popular research themes, we applied the same automated content analysis method to the submissions that were accepted into the second phase. We found five research themes (Table 10) that were the focus of an approximately similar number of submissions. In order to give a better insight in the discovered research themes, we provide a list of extracted keywords which were related to the topic of investigation and their theoretical approaches (Table 11), and also a list of extracted keywords related to the data sources, analysis techniques, and used metrics (Table 12).

Research theme 1: engagement and learning success

The main topics in this cluster are related to learners' participation, engagement, and behavioral patterns in MOOCs. Submissions in this cluster aimed to reveal the most suitable methods and approaches to understanding and increasing retention, often relying on peer learning and peer assessment. Studies encompassed a wide variety of courses (e.g., biology, mathematics, writing, EEG-enabled courses, art, engineering, mechanical) on diverse platforms. However, most of the courses, used in the studies from this cluster, were offered on the Coursera platform.

Table 9

Phase 2 Research Themes

Theme	Size	Accepted funding	Authors avg. (SD)	Citations avg. (SD)	Major Fields	Qualitative	Mixed	Quantitative
Cluster 1 Engagement and Learning Success	14	6 (42.9 %)	2.2 (1.3)	15.0 (9.8)	Education (14) Computer Science (4) Engineering(3)	1	3	10
Cluster 2 MOOC Design and Curriculum	14	2 (14.3 %)	2.9 (2.1)	20.2 (13.7)	Education (19) Computer Science (7) Engineering(4)	3	5	6
Cluster 3 Self-Regulated Learning and Social Learning	15	6 (40.0 %)	2.3 (0.9)	21.7 (9.2)	Education(25) Computer Science (3)	8	6	1
Cluster 4 SNA and Networked Learning	19	9 (47.4 %)	2.1 (0.8)	20.7 (15.6)	Education (23) Computer Science (5)	2	12	5
Cluster 5 Motivation, Attitude and Success Criteria	16	5 (31.2 %)	2.8 (1.1)	23.1 (9.2)	Education (25) Engineering (5) Social Sciences(4)	5	7	4
Total	78	28 (35.8 %)						

Table 10

Phase 2 Topics and Theoretical Approaches of Discovered Research Themes

Theme	Topics	Theoretical approaches
Cluster 1 Engagement and Learning Success	Student engagement Academic progress User behavior Actual participation Peer assessment High school students	Theory of planned behavior Motivational messages Flipped Classroom
Cluster 2 MOOC Design and Curriculum	Collaborative practices Participant observation Higher education Course implementation models Program evaluation Student-level analytics MOOC design Treatment group Online discussions Learning behavior	Flipped Classroom Interest-oriented learning Community-based learning Quality education resources Self-regulated learning Constitutive complexity theory Self-directed online learning MOOCulus HMM approach CoI framework Social interdependence theories
Cluster 3 Self-regulated and Social Learning	Social sciences Higher education Self-regulated learning At-risk learners Social learning Educational resources	Complexity theory Social learning theory Self-regulated learning Instructional design research Self-determination theory Goal theory Flipped classrooms
Cluster 4 SNA and Networked Learning	Social network analysis Learners interaction Higher education Discussion forums Online interactions Specific learner profiles Network formulation Asynchronous interaction Network structure P2P interactions	CSCL Summative assessment strategy Design-based research approach Complex connectivist learning Social Cognitive Theory Simple topic modeling Mixed Membership Stochastic Blockmodels
Cluster 5 Motivation, Attitude and Success Criteria	Learner motivation Intrinsic motivation Learning design Completion rates Teaching strategies High satisfaction rates Faculty attitude Evaluation plans	Data elicitation methodology Agile research methodology Adaptive learning design Actor network theory

Research theme 2: MOOC design and curriculum

Research proposals in this cluster were mostly concerned with improving learning process and learning quality and with studying students' personal needs and goals. Assessing educational quality, content delivery methods, MOOC design and learning conditions, these studies aimed to discover procedures that would lead to better MOOC design and curriculum, and thus improving learning processes. Moreover, many visualization techniques were suggested for investigation in order to improve learning quality. Courses suggested for the use in the proposed studies from this cluster were usually delivered by using the edX platform and the courses were in the fields of mathematics, physics, electronics and statistics. The cluster was also characterized by a diversity of data types planned for collection – from surveys, demographic data, and grades to engagement patterns and to data about brain activity.

Table 11

Phase 2 Research Characteristics of Discovered Research Themes

Theme	Data sources and measures	Analysis techniques/instruments
Cluster 1 Engagement and Learning Success	Students demographic characteristics EEG dataset TBP measures SAT scores Final grading score Mental state EEG brain activity Engagement patterns Latent patterns	Qualitative peer assessment Unsupervised learning Probabilistic Soft Logic Design-based research approach MOOC-scale peers grading Surveys Wireless EEG headset Quizzes Pre/post-tests
Cluster 2 MOOC Design and Curriculum	Student achievement data edX user data Case study data Assessment data Trace data Complex SQL data Activity Summary Data Preliminary clickstream analysis Complete clickstream data Archival data Educational metrics Students time allocation Students active participation	Assessment-based outcome measures Hidden Markov model Survey Interviews Qualitative field work Post-course surveys Open-ended narrative questions Student background surveys
Cluster 3 Self-regulated and Social Learning	Online discourses Survey responses Course behavior data Discussion forum data Diversity-related learning outcomes	Frame analysis Critical discourse analysis Content analysis Empirical qualitative research Association rule mining Mindset survey question

	Mindset score	Qualitative research interviews Entry survey In-depth interviews
Cluster 4 SNA and Networked Learning	Qualitative data collection Transactional data Social media data MOOC interaction data Click stream data Network analysis data Descriptive data Interactional data Course outcome data Coursera-based course data Longitudinal network data Longitudinal relational data Completion data Social graph data MOOCs learner metrics personality metrics social metrics standard statistic measure	Survival analysis Mixed research methods Collaborative Behaviors Analysis Interaction analysis Post-course data analysis Qualitative analysis Scale data analysis Probabilistic graphical models Text mining techniques with social network Learner analytics Quantitative research methods Real time analysis Focus groups Interviews Surveys D questionnaires Small group interviews
Cluster 5 Motivation, Attitude and Success Criteria	Publicly available data Course activity data Qualitative data Student performance data	Classification Confirmatory factor analysis Trace analysis Cluster analysis Structural equation modeling Qualitative data analysis Case study approach Interviews Surveys Open-ended assignments

Research theme 3: Self-regulated learning and social learning

Self-regulated learning, social learning, and social identity were the main topics discussed in the third cluster. Analyzing cognitive (e.g., memory capacity and previous knowledge), learning strategies and motivational factors, the proposals from this cluster aimed to identify potential trajectories that could reveal students at risk. Moreover, this cluster addressed issues of intellectual property and digital literacy. There was no prevalent platform in this cluster, while courses were usually in fields such as English language, mathematics and physics.

Research theme 4: SNA and networked learning

A wide diversity in analysis methods and data sources is one of the defining characteristics of this cluster (Table 12). Applying networked learning and social network analysis tools and techniques, the proposals aimed to address various topics, such as identifying central hubs in a course, or improving possibilities for students to gain employment skills. Moreover, learners' interaction profiles were analyzed in order to reveal different patterns of interactions between learners and instructors, among learners, and learners with content and/or underlying technology. Neither specific domain, nor platform was identified as dominant within the fourth cluster.

Research theme 5: Motivation, attitude and success criteria

The proposals within the fifth cluster aimed to analyze diverse motivational aspects and correlation between those motivational facets and course completion. Further, researchers analyzed various MOOC pedagogies (xMOOC, cMOOCs) and systems for supporting MOOCs (e.g., automated essay scoring), as well as attitudes of higher education institutions toward MOOCs. Another stream of research within this cluster was related to principles and best practices of transformation of traditional courses to MOOCs, as well as exploration of reasons for high dropout rates. The Coursera platform was most commonly referred to as a source for course delivery and data collection.

Phase 2 research methods.

Table 13 indicates that mixed methods was the most common methodological approach followed by purely quantitative research, which was used just slightly more than qualitative research. This suggests that there was no clear "winner" in terms of the adopted methodological approaches, and that all three types are used with a similar frequency. Also, the average number of authors and citations shows that the submissions mixed methods tended to have slightly more authors than quantitative or qualitative submissions, and that quantitative submissions had a significantly lower number of citations than submissions adopting both mixed and qualitative methods.

Table 10 shows that the submissions centered around engagement and peer assessment (i.e., cluster 1) used mainly quantitative research methods, while submissions dealing with self-regulated learning and social learning (i.e., cluster 3) exclusively used qualitative and mixed research methods. Finally, submissions centered around social network analysis (i.e., cluster 4) mostly used mixed methods, while submissions dealing with MOOC design and curriculum (i.e., cluster 2), and ones dealing with motivation, attitude and success criteria (i.e., cluster 5) had an equal adoption of all the three research methods.

Table 12

Phase 2 Distribution of Research Methodologies

Methodology	Submissions	Authors avg. (SD)	Citations avg. (SD)
Mixed	33 (42.3%)	2.7 (1.5)	21.8 (13.2)
Qualitative	19 (24.4%)	2.1 (0.9)	22.8 (12.10
Quantitative	26 (33.3%)	2.4 (1.2)	16.7 (10.3)
Total	78(100%)	2.5 (1.3)	20.3 (12.3)

Phase 2 demographic characteristics of the authors.

With respect to the primary research areas of the submission authors, Table 14 shows that education was the primary research field of the large majority of the authors and that computer science was the distant second. In terms of the average number of authors, we can see on Table 10 that submissions related to MOOC design and curriculum (i.e., research theme 2) and motivation, attitude and success criteria (i.e., research theme 5) had on average a slightly higher number of authors than the other three research themes. In terms of their number of citations, submissions dealing with the engagement and peer assessment had on average 15 citations, while the submissions about other research themes had a bit higher number of citations ranging from 20 to 23. Similar to Phase 1, in all research themes, the field of education was found to be the main research background of submission authors. This was followed by the submissions authored by computer science and engineering researchers, and in the case of submissions about motivation, attitude and success criteria, by social scientists. Finally, similar to Phase 1, we see the strong presence of researchers from North America, followed by the much smaller number of researchers from other parts of the world (Table 15).

Table 13

Phase 2 Top 5 Research Fields

Field	Authors
Education	106
Computer Science	21
Engineering	13
Industry	8
Social Sciences	6

Table 14

Phase 2 Geographic Distribution of the Authors

Continent	Authors	Authored proposals	Accepted proposals
Asia	17	4.64	0.14
Australia/NZ	11	4.25	1
Europe	40	15.66	4
North America	137	52.44	22.85
South America	3	1	0

Phase 2 citation analysis.

We calculated a total number of citations (Table 16) for each publication, and extracted a list of the most cited authors (Figure 3). We can observe that the most cited authors were not necessarily the ones with the highest betweenness centrality, but the ones whose research focus was most relevant from the perspective of the MRI initiative and researchers from different fields and with different research objectives.

We also extracted the citation network graph which is shown on Figure 4. At the centre of the network is L. Pappano, the author of a very popular *New York Times* article "The Year of the MOOC", as the author with the highest betweenness centrality value. The reason for this is that his article was frequently cited by a large number of researchers from a variety of academic disciplines, and thus making him essentially a bridge between them, which is clearly visible on the graph.

We also analyzed citation networks for each research theme independently and extracted common network properties such as diameter, average degree, path and density (Table 17).

Table 15

Phase 2 Most Cited Papers

Paper name	Citation count
Kizilcec, R. F., Piech, C. and Schneider, E. (2013). Deconstructing disengagement: analyzing learner subpopulations in massive open online courses.	15
Liyanagunawardena, T. R., Adams, A. A. and Williams, S. (2013). MOOCs: a Systematic Study of the Published Literature 2008-2012.	13
McAuley, A., Stewart, B., Siemens, G. and Cormier, D. (2010). The MOOC model for digital practice.	13
Breslow, L. B., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D. and Seaton, D. T. (2013). Studying learning in the worldwide classroom: Research into edX's first MOOC.	13
Siemens, G. (2005). Connectivism: A Learning Theory for the Digital Age.	12
Pappano, L. (2012).The Year of the MOOC.	10
Yuan L. and Powell S. (2013). MOOCs and Open Education: Implications for Higher Education.	9
Jordan, K. (2013). MOOC Completion Rates : The Data.	7
Belanger, Y. and Thornton, J. (2013). Bioelectricity: A Quantitative Approach. Duke University First MOOC.	7
Long, P. and Siemens, G. (2012). Penetrating the fog: analytics in learning and education.	6
Kop, R. (2011). The Challenges to Connectivist Learning on Open Online Networks: Learning Experiences during a Massive Open Online Course.	6
Daniel, J. (2012). Making Sense of MOOCs: Musings in a Maze of Myth, Paradox and Possibility.	6
Mackness, J., Mak, S. F. J. and Williams, R. (2010). The Ideals and Reality of Participating in a MOOC.	5
Means, B., Toyama, Y., Murphy, R., Bakia, M. and Jones, K. (2010).Evaluation of Evidence-Based Practices in Online Learning: A Meta-Analysis and Review of Online Learning Studies.	5

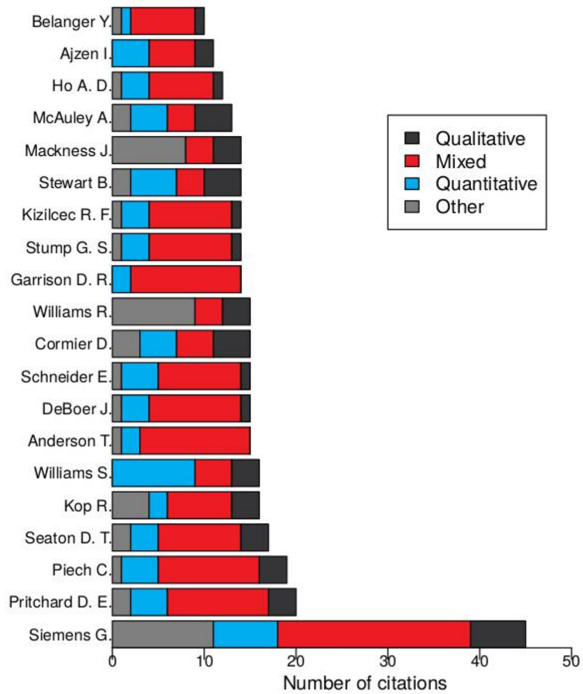

Figure 3. Phase 2 most cited authors

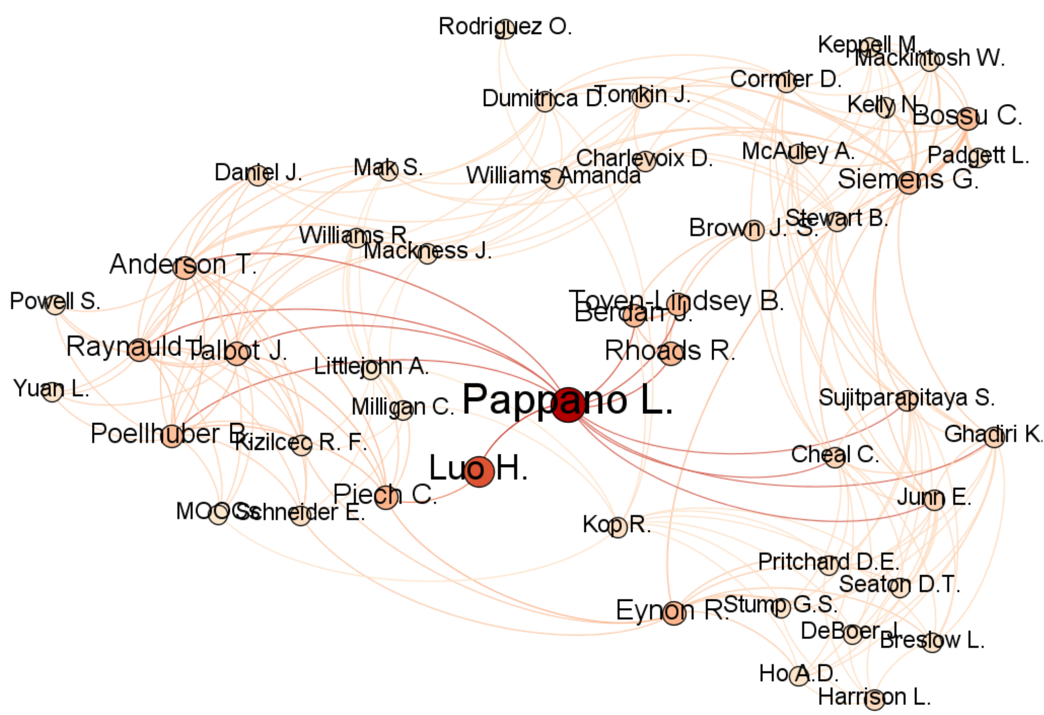

Figure 4. Phase 2 citation network.

Table 16

Phase 2 Citation Network Metrics

Cluster	Average degree (SD)	Diameter	Average shortest path (SD)	Density
Cluster 1 Engagement and Peer Assessment	4.6 (8.4)	8	4.5 (1.6)	0.014
Cluster 2 MOOC Design and Curriculum	5.3 (10.9)	9	4.3 (1.8)	0.017
Cluster 3 Learning Characteristics and Social Learning	5.4 (8.7)	7	4.1 (1.3)	0.023
Cluster 4 SNA and Networked Learning	4.9 (9.6)	8	3.9 (1.4)	0.015
Cluster 5 Motivation, Attitude and Success Criteria	6.9 (9.0)	8	3.7 (1.5)	0.033
Total	5.1 (7.3)	11	4.0 (1.3)	0.012

Phase 2 success factors.

Similar to the analysis in Phase 1, we wanted to see whether there was any significant correlation between the citation network centrality measures (Table 17) and the final submission acceptance rates. However, unlike in Phase 1, Spearman's rho did not reveal any statistically significant correlation at the $\alpha=0.05$ significance level.

Discussion

Emerging Themes in MOOC Research

The results of the analysis indicated a significant attention of the researchers to the issues related to MOOCs that have received much public (media) attention. Specifically, the issue of low course completion and high degree of student attrition was often pronounced as the key challenge of MOOCs (Jordan, 2013; Koller, Ng, Do, & Chen, 2013). Not only was the topic of engagement and learning success (Cluster 1 in Phase 2) identified as a key theme in the MRI submissions, but it was also identified as a theme that was clearly cross-cutting all other research themes identified in Phase 2, including motivation, attitudes and success criteria in Cluster 5, course design in Cluster 2, and learning strategies, social interaction, and interaction with learning resources in Cluster 3. With the aim to understand the factors affecting student engagement and success in MOOCs, the proposals had suggested a rich set of data collection methods – for example, surveys, physiological brain activity, knowledge tests, and demographic variables (see Table 12). The theory of planned behavior (TBP) (Ajzen, 1991) was found (see Cluster 1 in Table 11) as the main theoretical foundation for research of student engagement and learning success. While TBP is a well-known framework for studying behavioral change – in this case changing students intention to complete a MOOC and thus, increase their likelihood of course completion – it remains to be seen to what extent a student's intention can be changed if the student did not have an intention to complete a MOOC in the first place. What would be a reason that could motivate a student to change their intention in cases when she/he only enrolled into a MOOC to access information provided without intentions to take any formal assessments? In that sense, it seems necessary first to understand students' intentions for taking a MOOC, before trying to study the effects of interventions (e.g., motivational messages) on the students with different initial intentions.

The results also confirmed that social aspects of learning in MOOCs were the most successful theme in the MRI initiative (see Table 9). A total of 15 out of the 28 accepted proposals (Clusters 3 and 4) were related to different factors of social learning in MOOCs. Not only has it become evident recently that students require socialization in MOOCs through different forms of self-organization, such as local meet-ups (Coughlan, 2014) [7] and that social factors contribute to attribution in MOOCs (Rosé et al., 2014), educational research is also very clear about numerous educational benefits of socialization. The Vygotskian approach to learning posits that higher levels of internalization can be achieved through social interaction most effectively (Vygotsky, 1980). These benefits have been shown to lead to deeper approaches to learning and consequently to higher learning outcome (Akyol & Garrison, 2011). Moreover, students' positions in social networks have been found in the existing literature to have a significant positive effect on many important learning outcomes such as creative potential (Dawson et al., 2011), sense of belonging (Dawson et al., 2011), and academic achievement (Gašević, Zouaq, & Janzen, 2013). Yet, the lack of social interaction can easily lead to the sense of social isolation which is well documented as one of the main barriers in distance and online education (Muilenburg & Berge, 2001; Rovai, 2002). Finally, Tinto's (1997) influential theory recognizes social and academic integration as the most important factors of student retention in higher education.

[7] It is important to acknowledge that the importance of a "face-to-face contact with other students" was found in the Lou et al. meta-analysis (2006) of the literature – published in the period from 1985 to 2002 – about the effects of different aspects of distance and open education on academic success.

Research Methods in MOOC Research

The high use of mixed methods is a good indicator of sound research plans that recognized the magnitude of complexity of the issues related to MOOCs (Greene, Caracelli, & Graham, 1989). The common use of design-based research is likely a reflection of MOOC research goals aiming to address practical problems, and at the same time, attempting to build and/or inform theory (Design-Based Research Collective, 2003; Reeves, Herrington, & Oliver, 2005). This assumes that research is performed in purely naturalistic settings of MOOC offering (Cobb, Confrey, diSessa, Lehrer, & Schauble, 2003), always involves some intervention (Brown, 1992), and typically has several iterations (Anderson & Shattuck, 2012). According to Anderson and Shattuck (2012), there are two types of interventions – instructional and technological – commonly applied in online education research. Our results revealed that the focus of the proposals submitted to the MRI initiative was primarily on the instructional interventions. However, it is reasonable to demand from MOOC research to study the extent to which different technological affordances, instructional scaffolds and the combinations of the two can affect various aspects of online learning in MOOCs. This objective was set a long time ago in online learning research, led to the Great Media debate (Clark, 1994; Kozma, 1994), and the empirical evidence that supports either position (affordances vs. instruction) of the debate (Bernard et al., 2009; Lou, Bernard, & Abrami, 2006). Given the scale of MOOCs, a wide spectrum of learners' goals, differences in roles of learners, instructors and other stakeholders, and a broad scope of learning outcomes, research of the effects of affordances versus instruction requires much research attention and should produce numerous important practical and theoretical implications. For example, an important question is related to the effectiveness of the use of centralized learning platforms (commonly used in xMOOCs) to facilitate social interactions among students and formation of learning networks that promote effective flow of information (Thoms & Eryilmaz, 2014).

Our analysis revealed that the issue of the number of iterations in design-based research was not spelled out in the proposals of the MRI initiative (Anderson & Shattuck, 2012). It was probably unrealistic to expect to see proposals with more than one edition of a course offering given the timeline of the MRI initiative. This meant that the MRI proposals, which aimed to follow design-based research, were focused on the next iteration of existing courses. However, given the nature of MOOCs, which are not necessarily offered many times and in regular cycles, what is reasonable to expect from conventional design-based methods that require several iterations? Given the scale of the courses, can the same MOOC afford for testing out several interventions that can be offered to different subpopulations of the enrolled students in order to compensate for the lack of opportunity of several iterations? If so, what are the learning, organizational, and ethical consequences of such an approach and how and whether at all they can be mitigated effectively?

The data collection methods were another important feature of the proposal submissions to the MRI initiative. Our results revealed that most of the proposals planned to use conventional data sources and data collection methods such as grades, surveys on assessments, and interviews. Of course, it was commending to see many of those proposals being based on the well-established theories and methods. However, it was surprising to see a low number of proposals that had planned to make use of the techniques and methods of learning analytic and educational data mining (LA/EDM) (Baker & Yacef, 2009; Siemens & Gašević, 2012). With the use of LA/EDM approaches, the authors of the MRI proposals would be able to analyze trace data about learning activities, which are today commonly collected by MOOC platforms. The use of LA/EDM methods could offer some direct research benefits such as absence and/or reduction of self-selection and being some less unobtrusive, more dynamic, and more reflective of actual learning activities than conventional methods (e.g., surveys) can measure (Winne, 2006; Zhou & Winne, 2012).

Interestingly, the most successful themes (Clusters 3-4 in Phase 2) in the MRI initiative had a higher tendency to use the LA/EDM methods than other themes. Our results indicate that the MRI review panel expressed a strong preference towards the use of the LA/EDM methods. As Table 12 shows, the data types and analysis methods in Clusters 3-4 were also mixed by combining the use of trace data with conventional data sources and collection methods (surveys, interviews, and focus groups). This result provided a strong indicator of the direction in which research methods in the MOOC arena should be going. It will be important however to see the extent to which the use of LA/EDM can be used to advance understanding of learning and learning environments. For example, it is not clear whether an extensive activity in a MOOC platform is indicative of high motivation, straggling and confusion with the problem under study, or the use of poor study strategies (Clarebout, Elen, Collazo, Lust, & Jiang, 2013; Lust, Juarez Collazo, Elen, & Clarebout, 2012; Zhou & Winne, 2012). Therefore, we recommend a strong alignment of the LA/EDM methods with educational theory in order to obtain meaningful interpretation of the results that can be analyzed across different contexts and that can be translated to practice of learning and teaching.

Importance of Interdisciplinarity in MOOC Research

The analysis of the research background of the authors who submitted their proposals to the MRI initiative revealed an overwhelmingly low balance between different disciplines. Contrary to the common conceptions of the MOOC phenomena to be driven by computer scientists, our results showed that about 53% in Phase 1, 67% in Phase 2, about 67% of the finally accepted proposals were the authors from the discipline of education. It is not clear the reason for this domination of the authors from the education discipline. Could this be a sign of the networks to which the leaders of the MRI initiative were able to reach out? Or, is this a sign of fragmentation in the community? Although not conclusive, some signs of fragmentation could be traced. Preliminary and somewhat anecdotal results of the new ACM international conference on learning at scale indicate that the conference was dominated by computer scientists[8]. It is not possible to have a definite answer if the fragmentation is actually happening or not based on only these two events. However, the observed trend is worrying. A fragmentation would be unfortunate for advancing understanding of a phenomenon such as MOOCs in particular and education and learning in general, which require strong interdisciplinary teams (Dawson et al., 2014). Just as an illustration of possible negative consequences of the lack of disciplinary balance could be the theme of educational technology innovation (Cluster 1 in Phase 1) in the MRI initiative. As results showed, this theme resulted in no proposal approved for funding. One could argue that the underrepresentation of computer scientists and engineers in the author base was a possible reason for the lack of technological argumentation. Could a similar argument be made for Learning @ Scale regarding learning science and educational research contribution remains to be carefully interrogated through a similar analysis of the Learning @ Scale conference's community and topics represented in the papers presented at and originally submitted to the conference.

The positive association observed between the success of individual themes of the MRI submissions and citation network structure (i.e., diameter and average network path) warrants research attention. This significance of this positive correlation indicates that the themes of the submitted proposals, which managed to reach out to broader and more diverse citation networks, were more likely to be selected for funding in the MRI initiative. Being able to access information in different social networks is already shown to be positively associated with achievement, creativity, and innovation (Burt et al., 2013). Moreover, the increased length of network diameter – as shown in this study – was found to boost spread of behavior (Centola, 2010). In the context of the results of this study, this could mean that the increased diameters of citation networks in successful MRI themes were assessed by the MRI review panel as more likely to spread educational technology innovation in MOOCs. If that is the case, it would be a sound indicator of quality assurance followed by the MRI peer-review process. On the other hand, for the authors of research proposals, this would mean that trying to cite broader networks of authors would increase their chances of success to receive research funding. However, future research in other different situations and domains is needed in order to be able to validate these claims.

Conclusions and Recommendations

Research needs to come up with theoretical underpinnings that will explain factors related to social aspects in MOOCs that have a completely new context and offer practical guidance of course design and instruction (e.g., Clusters 2, 4, and 5 in Phase 2). The scale of MOOCs does limit the extent to which existing frameworks for social

[8] http://learningatscale.acm.org

learning proven in (online) education can be applied. For example, the community of inquiry (CoI) framework posits that social presence needs to be established and sustained in order for students to build trust that will allow them to comfortably engage into deeper levels of social knowledge construction and group-based problem solving (Garrison, Anderson, & Archer, 1999; Garrison, 2011). The scale of and (often) shorter duration of MOOCs than in traditional courses limits opportunities for establishing sense of trust between learners, which likely leads to much more utilitarian relationships. Furthermore, teaching presence – established through different scaffolding strategies either embedded into course design, direct instruction, or course facilitation – has been confirmed as an essential antecedent of effective cognitive processing in both communities of inquiry and computer-supported collaborative learning (CSCL) (Fischer, Kollar, Stegmann, & Wecker, 2013; Garrison, Cleveland-Innes, & Fung, 2010; Gašević, Adesope, Joksimović, & Kovanović, 2014). However, some of the pedagogical strategies proven in CoI and CSCL research – such as role assignment – may not fit to the MOOC context due to common assumptions that the collaboration and/or group inquiry will happen in small groups (6-10 students) or smaller class communities (30-40 students) (Anderson & Dron, 2011; De Wever, Keer, Schellens, & Valcke, 2010). When this is combined with different goals with which students enroll into MOOCs compared to those in conventional (online) courses, it becomes clear that novel theoretical and practical frameworks of understanding and organizing social learning in MOOCs are necessary. This research direction has been reflected in the topics identified in Cluster 4 of Phase 2 such as network formulation and peer-to-peer, online, learners and asynchronous interaction (Table 11). However, novel theoretical goals have not been so clearly voiced in the results of the analyses performed in this study.

The connection with learning theory has also been recognized as another important feature of the research proposals submitted to MRI (e.g., Clusters 3-5 in Phase 2). Likely responding to the criticism often attributed to the MOOC wave throughout 2012 not to be driven by rigorous research and theoretical underpinnings, the researchers submitting to the MRI initiative used frameworks well-established in educational research and the learning sciences. Of special interest were topics related to self-regulated learning (Winne & Hadwin, 1998; Zimmerman & Schunk, 2011; Zimmerman, 2000). Consideration of self-regulated learning in design of online education has been already recognized. To study effectively in online learning environments, learners need to be additionally motivated and have an enhanced level of metacognitive awareness, knowledge and skills (Abrami, Bernard, Bures, Borokhovski, & Tamim, 2011). Such learning conditions may not have the same level of structure and support as students have typically experienced in traditional learning environments. Therefore, understanding of student motivation, metacognitive skills, learning strategies, and attitudes is of paramount importance for research and practice of learning and teaching in MOOCs.

The new educational context of MOOCs triggered research for novel course and curriculum design principles as reflected in Cluster 2 of Phase 2. Through the increased attention to social learning, it becomes clear that MOOC design should incorporate factors of knowledge construction (especially in group activities), authentic learning, and personalized learning experience that is much closer to the connectivist principles underlying cMOOCs (Siemens, 2005), rather than knowledge transmission as commonly associated with xMOOCs (Smith & Eng, 2013). By triggering the growing recognition of online learning world-wide, MOOCs are also interrogated from the perspective of their place in higher education and how they can influence blended learning strategies of institutions in the post-secondary education sector (Porter, Graham, Spring, & Welch, 2014). Although the notion of flipped classrooms is being adopted by many in the higher education sector (Martin, 2012; Tucker, 2012), the role of MOOCs begs many questions such as those related to effective pedagogical and design principles, copyright, and quality assurance.

Finally, it is important to note that the majority of the authors of the proposals submitted to the MRI were from North America, followed by the authors from Europe, Asia, and Australia. This clearly indicates a strong population bias. However, this was expected given the time when the MRI initiative happened – proposals submitted in mid-2013. At that time, MOOCs were predominately offered by the North American institutions through the major MOOC providers to a much lesser extent in the rest of the world. Although the MOOC has become a global phenomenon and attracted much mainstream media attention – especially in some regions such as Australia, China and India as reported by Kovanovic et al. (2014) – it seems the first wave of research activities is dominated by researchers from North America. In the future studies, it would be important to investigate whether this trend still holds and to what extent other continents, cultures, and economies are represented in the MOOC research.

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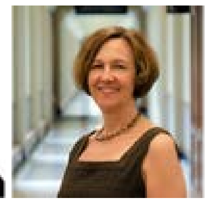
Democratizing Higher Education: Exploring MOOC Use Among Those Who Cannot Afford a Formal Education

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Abstract

Massive open online courses ("MOOCs") provide free access to higher education for anyone with Internet access. MOOCs are considered a means for democratizing education. These courses will hopefully provide an opportunity for individuals to learn from the best educators in the world, as well as help expand their personal networks, and facilitate their career development. However, research thus far shows that the majority of people taking advantage of these courses are already employed, have post-secondary degrees, and have encountered few barriers related to the affordability of higher education. Little is known about MOOC learners with financial constraints and who do not fit the typical profile of MOOC learners. This paper presents the results of the analysis of data from six Coursera courses offered by the University of Michigan from fall 2012 through winter 2013. In this analysis learners who self-identified as being unable to afford to pursue a formal education (the target group) were contrasted to other learners (the comparison group) in terms of demographics, motivations, course enrollment, engagement and performance. Learners in the target group were primarily male and over 25 years old. A statistically significant portion of the target group held less than a 4-year college degree than the comparison group. Target learners were also significantly underrepresented in the enrollment of the courses examined here. Although the comparison group had a significantly higher completion rate overall than the target group, the target group had a statistically significant higher rate of completing courses with certificates of distinction. This article provides a discussion of these results and suggests how MOOCs could be adapted to better address the needs of learners who feel financially unable to pursue a more traditional path to a post-secondary education.

Keywords: Massive open online courses; education; online learning; affordability

Introduction

Massive open online courses (MOOCs) are seen as an opportunity to gain access to education and professional development, and to develop new skills to prepare for high-paying jobs (Pappano, 2012). Recent articles on MOOCs in both the scholarly literature and the popular press emphasize the fact that hundreds of thousands of people around the world now have access to courses offered by elite universities (Lewin, 2012). Information and communication technologies have increased opportunities for higher education, though the key beneficiaries are individuals from affluent families from the Western Province (Liyanagunawardena, 2012). In addition, research thus far consistently shows that the people taking advantage of MOOCs are already employed, young, well educated, predominantly male, from developed countries, have higher levels of formal education, and are unlikely to encounter barriers related to the affordability of higher education (Christensen, Steinmetz, Alcorn, Bennett, Woods, Emanuel, 2013). In short, the individuals expected to benefit most from MOOCs are inadequately represented among the early adopters of this new form of education (Christensen et al., 2013). Although MOOCs are seen as one possible path toward upward mobility, few studies have examined whether and how the populations with the most to gain leverage these resources. Therefore the goal of this study was to address the following question to complement prior research: How do the demographics, enrollment, personal motivations, performance and engagement of learners unable to afford a formal education compare or contrast to learners who do not report being motivated by financial constraints?

This paper provides the results of a comparison between MOOC learners who self-identified as being unable to afford to pursue a formal education (the target group) with other learners (the comparison group), looking specifically at demographic data and motivations across 11 Coursera offerings from fall 2012 to winter 2013. The results detailed here contribute a better understanding of an understudied and underrepresented group. The aim is to determine how MOOCs might better serve those who feel financially unable to pursue a more traditional path to post-secondary education studies.

Related Work

Massive open online courses are considered a means for democratizing education (Lewin, 2012; Wulf, Brenner, Leimeister, 2014). MOOCs address an unlimited number of participants ("massive"); are offered free of charge or impose only low participation fees ("open"); are not dependent on location as they are available via the Internet ("online"); and the content consists of instructional lectures and assessment ("courses") (Wulf, Brenner, Leimeister, 2014; Clow, 2013; McAuley et al., 2010; Vardi, 2012). However, research shows that MOOCs are reaching a fairly homogeneous population and that those thought to benefit most from these courses are underrepresented in course enrollments (e.g., Christensen, Steinmetz, Alcorn, Bennett, Woods, & Emanuel, 2014). Therefore, it is unclear how people who are financially constrained, who may be unemployed, and who have less formal education are taking advantage of these courses. The question of whether they can benefit from participating in this new educational context also remains open.

In a systematic review of 45 peer-reviewed papers in the MOOC-related literature published between 2008-2012, Liyanagunawardena, Adams, and Williams (2013) found that the majority of articles discussed MOOC challenges and trends. McAuley, Stewart, Siemens, and Cormier (2010) advocated for a clear research agenda to help evaluate both the feasibility and the potential of the MOOC model for opening up access to higher education and the circumstances in which MOOCs might achieve this potential. They identified several open questions and challenges, such as the role for MOOC accreditation, understanding depth versus breadth in MOOC participation, understanding the conditions in which MOOC participation can expand beyond those with broadband access and advanced social networking skills, and the viability of MOOCs from an economic perspective. Understanding how underrepresented learners compare to the majority of MOOC learners in terms of demographics, motivations, engagement and performance could help to evaluate the feasibility of the conditions by which MOOCs might achieve their potential for democratizing education.

Researchers from the University of Pennsylvania analyzed more than 400,000 surveys from individuals enrolled in 32 Coursera courses (Christensen, Steinmetz, Alcorn, Bennett, Woods, Emanuel, 2013). In these courses, 83% of the registered learners had two-or four-year degrees, and of those, 44% had some graduate education. According to an analysis of 17 online courses offered on the edX platform, Ho et al. (2014) found that of those reporting, the most typical edX MOOC learners were males with bachelor's degrees who are 26 and older (31% of learners). Learners reporting their gender as female represented 29%. Learners enrolling in these MOOCs appeared to be diverse in terms of highest education achieved (33% reported high school and lower), age (6.3% reported being 50 or older) and 2.7% of the students had mailing or IP address from the least developed countries as listed on the United Nations (Ho, Reich, Nesterko, Seaton, Mullaney, Waldo & Chang, 2014). The authors reported that despite the low percentages of learners from typically underserved populations, these courses were still reaching a large number of these learners and that the edX MOOCs were attracting diverse audiences.

MOOCs are still relatively new (Clow, 2013) and unexplored in the literature on distance education and online distance learning. Many research questions are still open in regard to the learning analytics on MOOCs and understanding trends such as the high drop rates (Clow, 2013). In particular, future research should further investigate the types of learners taking advantage of MOOCs and their motivations. The research discussed in this article provides an understanding of a population that has not yet been studied—

learners who report being unable to afford a formal education. The data for this study comes from learners who registered in Coursera courses offered by the University of Michigan, a large midwestern university in the U.S. The goal of the research was to address the following research question: How do the demographics, enrollment, personal motivations, performance and participation of learners compare or contrast to learners who do not report being motivated by financial constraints? This article provides the results of this analysis, and suggests how MOOCs could be adapted to better meet the needs of this population. The results help to further develop hypotheses regarding the performance and demographics of these populations across multiple MOOC courses, platforms, and universities.

Methodology

As this study was exploratory in nature, statistical methods consisted of a series of comparative analyses between the target and the comparison group. These data were collected from the demographic surveys jointly administered by Coursera and the University of Michigan at the beginning of six courses (see Table 1). The surveys were voluntary and could be answered at any time during the course session. These surveys were designed to provide learner demographic information and their motivation for taking the MOOC (see Table 1, Question #3 for a complete list of motivations, and note that learners could select more than one answer). Any learner who included the answer indicating that they were unable to afford a formal education were classified as the “target group” for analyses. The “comparison group” comprised of those learners who selected any of the reasons other than affordability for enrolling in the course. Although determining the target group on the basis of a single survey question does not reveal possible variability in what affordability means to respondents, affordability was the major factor identifying underrepresented learners in previous MOOC research.

Course enrollment, engagement, and performance data was available via the data provided by the MOOC platform. Course engagement data included whether learners accessed course material, watched videos and engaged in discussion forums. In terms of forum engagement, learners could engage in four distinct activities: view a forum, view a thread, up vote a thread or down vote threads. Forum posting data was not readily available and does not appear in this analysis. Course performance data is available through grades achieved in the course. There were two types of course completion certificates—a basic “certificate of completion” and a “certificate of completion with distinction.” In general, earning a certificate required completion of the course with a minimum grade, or meeting a set of requirements set by each instructor; earning a certificate of distinction required passing with a higher grade threshold (which varied from course to course). Before discussing the results of the analysis, details of the course survey are presented next, as well as an overview of the courses analyzed.

Table 1

Survey Questions Used in Analysis

1. What is your gender? (open ended)

2. What is your age?	☐ Under 18	☐ 18-24	☐ 25-34
	☐ 35-44	☐ 45-54	☐ 55+
	☐ I prefer not to answer		

3. Which options best describe your motivations for taking this class? (please check all that apply)

☐ Cannot afford to pursue a formal education	☐ Supplement other college/university courses	☐ Geographically isolated from educational institutions
☐ Extending current knowledge of the topic	☐ General interest in the topic	☐ Decide if I want to take college/university classes on the topic
☐ Professional development	☐ Interest in how these courses are taught	

4. What is your highest level of education?

☐ Some high school	☐ High school	☐ Some college
☐ Associate's degree (2 year's of college)	☐ Bachelor's degree (BA/BS 4-year's of college)	☐ Master's degree

5. What is your current occupation? Select all that apply

☐ Student	☐ Faculty	☐ Teacher
☐ Other		

Survey and Course Overview

Survey responses were gathered from multiple offerings of six distinct courses offered in the fall of 2012 through the winter of 2013, for a total of 11 course offerings. These courses were 5 to 15 weeks long and taught by university professors at the University of Michigan. The advertised workload for the courses ranged from 4-12 hours per week. The courses were classified into three categories: 1) Humanities, 2) Economics and Finance, and 3) Technology. Specific course names are included in Table 2.

Table 2

Summary of Courses Offered

Course Type	Course Names	Course #
Humanities	Fantasy and Science Fiction	1
Economics and Finance	Model Thinking	2
	Intro to Finance	3
Technology	Internet, History, Technology and Security	4
	Social Network Analysis	5
	Securing Digital Democracy	6

Results

In total, 666,407 learners registered for the six courses and approximately 6.3% (N=42,097) took the demographic surveys. Note that not all of the questions were answered by every student thus the *n* varies by item (see survey response rates in Table 3). Only 9.08% (N=3,812) of those completing surveys represented the target population (i.e., stated that they were not able to afford a formal education).

Table 3

Number of Survey Participants and Response Rates for each Course by Term Offered

Course type	Course #	#Participants	
		Fall 2012	Winter 2013
Humanities	1	37,118 (2.90%)	23,318 (.77%)
Economics and Finance	2	102,802 (2.47%)	38,429 (17.50%)
	3	125,332 (5.42%)	89,362 (9.50%)
Technology	4	41,683 (10.94%)	34,218 (18.67%)
	5	61,754 (1.97%)	35,363 (10.29%)
	6	19,582 (2.43%)	*NA

Note. *Survey responses were unavailable.

Table 3 shows that the courses with the highest survey response rates occurred in the winter of 2013. While the causes of these variations in response rates are unclear, factors such as the popularity of MOOCs in general or the commitment of learners after evaluating the courses the first time around may reflect response rates.

The next section provides the results of the demographic survey, motivations for enrollment (e.g., other than an inability to afford a formal education), and course enrollment details. The section concludes with details about how the target population performed relative to the comparison group. Where applicable, statistically significant differences between the target and comparison groups are specified.

Demographics

Overall, 41,636 learners that responded to the question of gender and 68.65% (N=28,585) were male. Of the 41,734 learners that responded to the question of age, the largest age group taking courses was 25-34 (39.78%, N=16,603), and the second largest age group was 18-24 (22.67%, N=9,461). For the total number of learners responding to the survey, 99.68% (N=41,961) answered the question regarding their motivations for taking the course. Of these, approximately 9.08% (N=3,812) were in the target population. The remaining 90.92% (N=38,149), those in the comparison group, did not select affordability as their motivation for taking the courses.

Tables 4-1 and 4-2 provide a breakdown of the gender and age of the target and comparison groups.

Table 4-1

Gender Breakdown for Learners in the Target vs. Comparison Groups

Target (i.e., Cannot afford, N=3,762)			Comparison (i.e., Other, N=37,788)		
Gender	Count	Percentage	Gender	Count	Percentage
Male	2,467	65.58%	Male	26,053	68.95%
Female	1,295	34.42%	Female	11,735	31.05%

Table 4-2

Age Breakdown for Learners in the Target vs. Comparison Groups

Target (i.e., Cannot afford, N=3,798)			Comparison (i.e., Other, N=37,855)		
Age	Count	Percentage	Gender	Count	Percentage
18-24	764	20.12%	Male	8,678	22.92%
25-34	1,690	44.50%	Female	14,883	39.32%

The target and comparison groups are relatively the same in terms of gender and age. Learners in both groups were primarily male (~70%) and between 25-34 years old. This finding is consistent with the age and gender demographics reported in prior research (Christensen, Steinmetz, Alcorn, Bennett, Woods, Emanuel, 2013).

Overall, 37,148 learners responded to the question of motivation and country of origin. Table 5 provides a summary of the country of origin of both groups.

Table 5

**Country of Origin, Count and Percentage of Enrollment for Learners in the Target vs. Comparison Groups*

Target (i.e., Cannot afford, N=3,191)			Comparison (i.e., Other, N=33,957)		
Country	Count	Percentage	Country	Count	Percentage
US	1,065	33.38%	US	9,615	28.32%
IN	236	7.40%	IN	2659	7.83%
GB	154	4.83%	BR	1,502	4.42%

*Note that the survey asks for country of origin rather than the current country of residence.

The majority of learners in the target and comparison groups were from the United States, followed by India. Great Britain was third among the target group while Brazil was third among the comparison group. Consistent with prior research, the single largest group of learners is from the U.S., but there were also learners taking courses from developing regions (Ho, Reich, Nesterko, Seaton, Mullaney, Waldo, & Chuang, 2014).

Educational Achievement

Overall, 41,709 participants responded to the survey question regarding their motivations for taking the course and their highest educational degrees achieved (Figure 1 questions 3 and 4). See Table 6 for details.

Table 6

Degree Achievement for Learners in the Target and Comparison Groups

Group	Target (i.e., Cannot afford, N=3,790)	Comparison (i.e., Other, N=37,919)
Some high school	72 12.33%	512 87.67%
High school	355 13.40%	2,294 86.60%
Some college	593 17.78%	2,742 82.22%
Associate's degree (2 years of college)	251 14.14%	1,524 85.86%
Bachelor's degree (BA/BS, 4 years of college)	1,519 9.83%	13,931 90.17%
Master's degree	834 5.95%	13,194 94.05%
Professional degree (MD, JD)	85 5.91%	1,354 94.09%
Doctoral degree	81 3.31%	2,368 96.69%

As shown in Table 6, approximately one third (33.63%, N=14,028) of all individuals responding to the survey reported that their highest degree achieved was a master's degree, and 37.04% (N=15,450) had a bachelor's degree. These results also show that a statistically significantly higher percentage of the target population reported having a bachelor's degree than those in the comparison group (40.08% vs. 36.74%, $z=4.06$, $p<.01$).

In addition, a larger majority of target learners had bachelor's degrees (40.08% N=1,519) than master's degrees (22.01% N=834), which is significantly different from the comparison group (36.74% N=13,931 vs. 34.80% N=13,194 respectively) ($z=52.18$ $p<0.01$). In fact, learners in the comparison group had a statistically significant higher proportion of advanced degrees (e.g., master's degree and higher) than the target group (44.61% vs. 26.39%, $z=21.61$, $p<0.01$), while a statistically significant portion of the target group had less than a four-year college degree in contrast to the comparison group (33.54% vs. 18.65%, $z=21.84$, $p<0.01$).

Motivations

Figure 1 shows a comparison of the reported motivations (excluding the ability to afford a formal education) for taking MOOCs between the target and comparison populations (N=42,097).

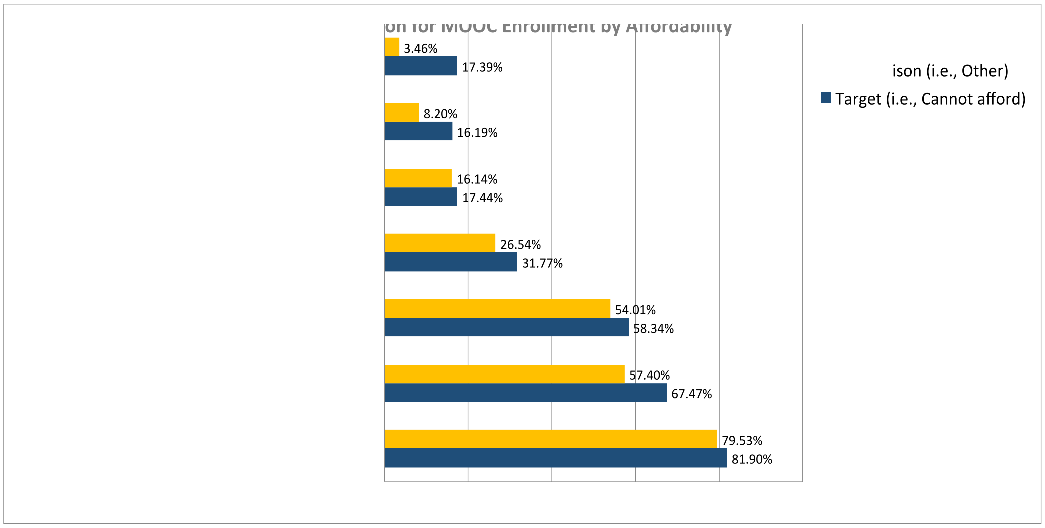


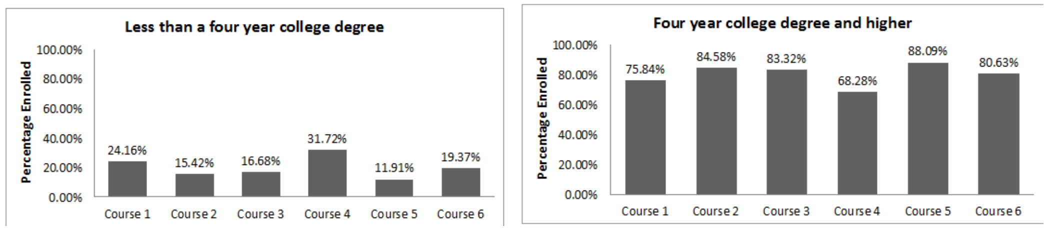
Figure 1. Additional motivations of learners based on affordability.

Given the large number of learners, all differences were statistically significant at the $p<0.01$ level (except to supplement other college/university classes/courses). The target learners, however, were five times more likely to indicate being motivated to take courses due to issues of geographic isolation than the comparison learners. The target learners were twice as likely to indicate being motivated to decide if they wanted to take college/university classes on the topic.

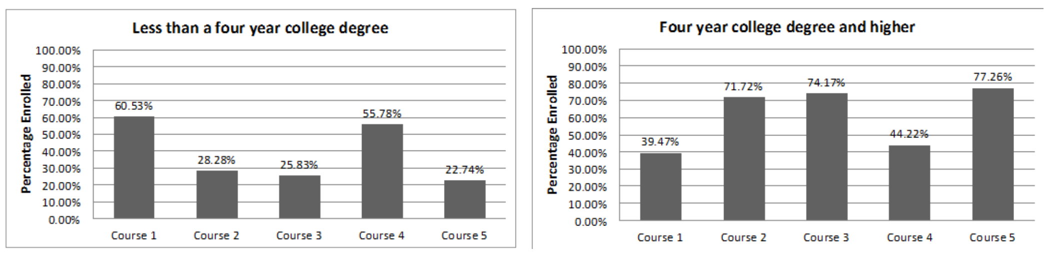
Course Enrollment

Course enrollment data (Figure 2) was analyzed based on education level in addition to affordability to compensate for any barriers to entry in terms of course difficulty.

All learners:



Target Learners:



Comparison Learners:

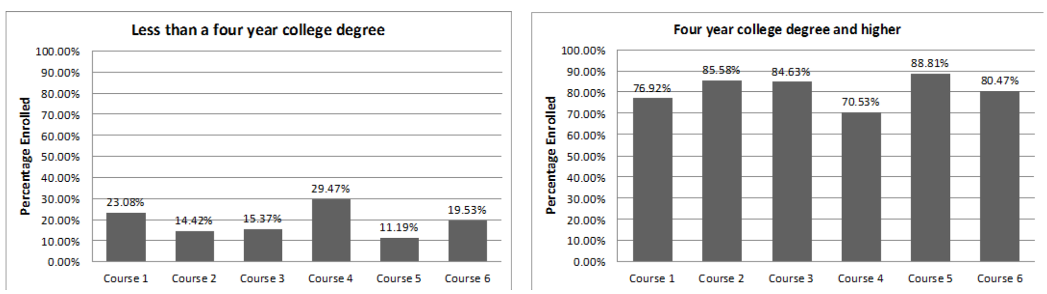


Figure 2. Percentage of course enrollment by degree achievement.

Note. Course 1: Fantasy and Science Fiction

Course 2: Model Thinking

Course 3: Introduction to Finance

Course 4: Internet, History, Technology and Security

Course 5: Social Network Analysis

Course 6: Securing Digital Democracy

Figure 2 shows that the two courses with the highest enrollment percentage for those with less than a 4-year degree across both target and comparison learners were Courses 4, which is a basic, technology-related course and 2 (Economics). By contrast, the highest percentage of enrollment for those with 4-year degrees and higher was Course 5, a more advanced technology course, followed by Courses 2 (Economics) and 3 (Finance).

Table 7 provides details regarding the actual number and percentage of the enrollment of each course per term offered. Note that none of the learners enrolled in the Humanities and Technology courses offered in the fall 2012 term reported an inability to afford a formal education (Table 7).

Table 7

Representation of Target and Comparison Groups by Course

Course type	Term	Target learners	Percentage of target enrolled	Comparison learners	Percentage of comparison enrolled
Humanities	Fall 2012	-	0.00%	3,607	100.00%
	Winter 2013	688	9.99%	6,199	90.01%
Economics and Finance	Fall 2012	847	12.52%	5,917	87.48%
	Winter 2013	1,062	12.54%	7,407	87.46%
Technology	Fall 2012	-	0.00%	6,239	100.00%
	Winter 2013	1,215	12.16%	8,780	87.84%
Grand total		3,812	9.08%	38,149	90.92%

Despite the low percentage of the target group in the overall sample, results showed a significant increase in the population over each course term offered (Table 7).

To better understand how issues of affordability may interact with educational attainment, Table 8 provides details regarding which courses may have attracted target learners who held less than a 4-year degree. Course 6 was removed from the table as survey responses were unavailable for winter 2013.

Table 8

Percentage of Learners in the Target Group Who Have Less than a 4-year Degree by Course

	Course 1	Course 2	Course 3	Course 4	Course 5
Fall 2012	22.41%	12.60%	14.42%	26.99%	9.50%
Winter 2013	34.64%	16.47%	18.48%	35.12%	12.72%
z-statistic	z=-3.54, $p<0.01$	z=-4.57, $p<0.01$	z=-6.67, $p<0.01$	z=-8.98, $p<0.01$	z=-2.99, $p<0.01$

As shown in Table 8, target learners with less than 4-year degrees had the highest enrollments in Courses 1 (Fantasy and Science Fiction) and 4 (Internet, History, Technology and Security). In addition to Humanities, these students are enrolling heavily into technology courses, which may suggest areas of future research. In fact, the increase in enrollment from fall 2012 to winter 2013 is statistically significant. Details of enrollment suggest that helping these populations may require access to courses that provide marketable skills.

Engagement and Performance

Log data of student activity in the course was used to analyze the participation, or engagement and performance between the two groups. These data included the number of times learners watched videos and completed assessments, forum engagement as well as the outcome earned in each course (no certificate, certificate, certificate of distinction). Overall, 48.88% of those that registered, including those not completing the surveys (N=325,743 N_{total} = 666,407), performed some activity within the course (e.g., actually watched a video, up or downvoted a thread, viewed a thread or a forum, looked at course materials and/or conducted an assessment). Consistent with prior research on MOOC completion rates (Christensen, Steinmetz, Alcorn, Bennett, Woods, Emanuel, 2013; Ho, Reich, Nesterko, Seaton, Mullaney, Waldo & Chuang, 2014), only 4.40% of all learners registered for these courses completed them and earned a certificate. Table 9 details the course completion results based on affordability.

Table 9

Level of Completion Based on Affordability

Achievement level	Target (i.e., Cannot afford, N=3,812)		Comparison (i.e., Other, N=38,149)	
	Count	Percentage	Count	Percentage
Certificate with distinction	339	9.11%	2,274	6.09%
Certificate only	716	19.24%	13,645	36.58%
None (e.g., did not complete)	2,757	71.65%	22,230	57.33%

There were no significant differences between the two groups' engagement in terms of watching videos, accessing course materials and/or conducting assessments. However, as measured by the total count of forum activities (up vote, down vote, view thread and view forum), participation among the target population (94.65%) was significantly less than the percentage of the comparison population (96.68%, z=-6.5, p<0.01). In addition, those in the comparison group had a higher percentage of course completion (36.58% vs. 19.24%, z=21.07, p<0.01). Despite these findings, a higher percentage of the target group completed a course with a certificate of distinction than the comparison group (9.11% vs. 6.10%, z=7.18, p<0.01).

Summary of Results

In summary, the demographics of learners from both groups were similar in coarse grain terms of gender (i.e., majority male), age (25-34 years old), and country of origin (i.e., majority U.S.), and are consistent with demographics reported in prior research (Christensen, Steinmetz, Alcorn, Bennett, Woods, Emanuel, 2013; Ho, Reich, Nesterko, Seaton, Mullaney, Waldo & Chuang, 2014). The demographic results also showed that the second highest percentage of target and comparison learners was from India, which provides evidence of learners from developing regions (Ho, Reich, Nesterko, Seaton, Mullaney, Waldo & Chuang, 2014).

In terms of educational achievement, results showed that a statistically significant portion of the target group (33.54%, N=1,271) had less than a four-year college degree in contrast to the comparison group (18.65%, N=7,072). Similar findings have been reported in a more focused study (Dillahunt, Chen & Teasley 2014). Target learners were also significantly more motivated to enroll in MOOCs than the comparison learners for all reasons except to supplement other courses.

While learners in the target group primarily enrolled in Economics and Finance, those with less than a four-year degree enrolled at higher rates in the courses with content focused on basic technology. Consistent with the fact that they had higher levels of education, the comparison learners had higher enrollment in the more advanced technology course. Nevertheless, there was an indication that the percentage of learners indicating an inability to afford a formal education had increased with each offering of the course (e.g., 12% increase in Course 1, 4% increase in Courses 2 and 3, 8% in Course 4 and 3% in Course 5 per Table 8).

Finally, and perhaps the most interesting result, although comparison learners had a higher completion rate overall, target learners had a significantly higher rate of completing courses with certificates of distinction (36.58% vs. 19.24%, $z=21.07$, $p<0.01$). This is despite the finding that participation among the target population was significantly less than the percentage of the comparison population. These results contribute insight into an unexplored MOOC population and additional insight into these learners' demographics, motivations, enrollment and performance; however, these findings raise additional questions and directions for future research.

Discussion and Limitations

The motivation behind this work was to understand the differences in demographics, motivations, course enrollment, and engagement and performance between learners who enrolled in a MOOC for reasons related to the affordability of traditional higher education as compared with learners who enrolled for reasons other than affordability. While the target learners could potentially reap the most economic benefit from taking these courses, the study findings show that this group only represents 9.08% of the surveyed population. A promising finding is that when these learners do complete a MOOC, they are more likely to earn a certificate with distinction than those who enrolled in the MOOC for reasons other than educational affordability. Understanding more detail about the motivations of these individuals is worth further investigation. For example, are these individuals primarily motivated for professional development? If so, are they specifically motivated to transition to new jobs, or to refresh their current skillset? Are the key differences in motivations between the target learners from the U.S. versus other regions related to geographic locations? These questions were beyond the scope of this initial exploration and fully understanding these findings will be aided by qualitative data focused on the nuances behind affordability.

Study Limitations

Perhaps the most significant limitation of this study is the potential for sampling bias inherent in opt-in surveys. Specifically, the survey method lends itself to a self-selection bias where learners choosing to respond to the pre-course surveys are usually more likely to be active course participants. In addition, those with the ability to respond to these surveys were more likely to respond—it is possible that those underrepresented populations which this study was designed to explore were the least likely to complete the surveys due to issues of affordability, accessibility and time. For example, certain regions may have intermittent Internet access or impose fees based on the amount of time spent online. Secondly, the reliability and accuracy of survey responses are always uncertain, and the issue of "affordability" is relative. For example, indicating, "I cannot afford to pursue a formal education" could mean that someone cannot afford to pursue a formal education financially, but it could also be interpreted as "I cannot afford to take time out of my schedule to pursue a formal education". It is also possible that some learners from the comparison group were not able to afford a formal education but they chose not to select this answer in the survey. Finally, the study data is limited to data from courses offered by a single U.S. university, though with a worldwide audience. Despite these limitations, the results of the analysis do offer an initial insight into an underrepresented and unexplored population of learners. These limitations alone provide implications for reaching underrepresented learners in the future.

Future MOOC Research

MOOCs are considered a means for democratizing education. An open question and challenge is to understand the feasibility of the MOOC model for opening up access to higher education and the potential to do so (McAuley, Stewart, Siemens & Courmier, 2010). The demographic results of this study are consistent with prior research showing that MOOCs are primarily taken by well-educated males, 26 years and older, from developed regions and who are unlikely to encounter financial constraints for pursuing their education. Learners who have less formal education, women, older adults, individuals from developing regions, and those with financial constraints, are underrepresented in MOOCs.

As mentioned in the study limitations, leveraging the survey to understand demographics and motivations of MOOC learners presents sampling bias and difficulties in reaching targeted populations. To better understand the factors related to issues of affordability, future research should explore whether and how MOOC platforms can capture more detailed information about learners during their activity and engagement in the courses. For example, is there a way to determine if learners are accessing courses via broadband, mobile, dial-up or from public facilities such as libraries, Internet cafes (which may be more common in developing regions), or universities? How can statistical models be used to detect enrollment of learners from these populations? What features can be used to identify these learners and barriers they may face (e.g., IP address to identify location, engagement trends, the type of technology being used to access the MOOCs)? What interventions could reduce these barriers?

Christensen, Steinmetz, and Alcorn (2013) describe a lack of technological access as the key reason poor people have not taken the opportunity to study online. Indeed research reveals that information and communication technologies have increased opportunities for higher education, although primarily for those individuals from affluent families from the Western Province (Liyanagunawardena, 2012). In an overview of the educational developments in open, distance, and technology-facilitated learning to reach world-wide populations deprived of education, Gulati found that new technologies have done little to help deprived groups gain access to educational opportunities (2008). Gulati's research has shown that these groups continue to be marginalized due to their lack of access to basic education and adequate learning resources. However, the rapid growth of mobile devices in developing countries may enhance the development of mobile learning to educate the masses (Gulati, 2008).

With worldwide penetration of the mobile-broadband subscriptions—almost 3 billion Internet users, two-thirds from the developing world and mobile-broadband uptake growing at double-digit rates by the end of 2014 (ITU, 2014)—access constraints may be declining. It is unclear, however, whether learners are leveraging mobile phones to access MOOC content. The results from this research suggest that financially constrained learners are finding ways to access these courses though these possibly represent the most motivated and the most affluent learners in certain regions. A better understanding of the methods in which learners access these courses could help to further understand these issues.

Although access is a concern, another issue could be a lack of awareness of the potential benefits MOOCs could offer. It is unclear how learners find out about MOOC courses and interesting to know whether sources differ from learners from the target and comparison groups. This could help to understand how information about the courses is currently being disseminated within these learner communities. Advertising MOOCs via billboards, radio and television, job placement offices, Internet cafes and libraries could help to raise awareness to the people who might benefit most from MOOCs. Although not discussed in the context of this study, it is also unclear whether and the extent in which English as the primary language of instruction in MOOCs presents access barriers to learners from developing and non-English speaking regions.

Finally, many unknowns still exist; including new pre-course survey questions could shed additional light on those learners that choose to complete the surveys. For example, requesting specific occupation information, current salary, place of degree attainment, and job type (e.g., full-time, part-time) could be beneficial. Understanding these factors could help to tease apart information about each cohort of learners and how these cohorts change over time. As mentioned earlier, exploring MOOC features to detect details such as methods of access and creating new models to predict when these learners engage could offer additional insight to ways to better meet the needs of these populations.

Conclusion

The aim of this study was to address the question: How do the demographics, enrollment, personal motivations, performance and engagement of learners unable to afford a formal education compare or contrast to other learners? Results from six Coursera courses offered by the University of Michigan from fall 2012 through winter 2013 show that while learners who self-reported an inability to afford a formal education were majority males, primarily over 25, they also

1. had a significant portion of learners with less than a four-year college degree than learners in the comparison group (33.54% vs. 18.65%, $z=21.84$, $p<0.01$);

2. were generally more motivated to enroll in MOOCs than those in the comparison group due to issues of geographic isolation (five times more likely to select this motivation than comparison) and deciding if they wanted to take college/university classes on the topic (twice as likely to select this motivation than comparison);

3. were significantly more likely to be awarded a certificate of achievement (9.11% vs. 6.10%, $z=7.18$, $p<0.01$) than those in the comparison group.

The goal of this research was to explore underrepresented MOOC populations as a starting point to better understand how to open up access to higher education to economically constrained populations. Future work includes obtaining more qualitative data about targeted learners via interviews to better understand their MOOC experiences, whether their goals are to obtain certificates with distinction and why, and investigating models that help to predict targeted learners. Future work also includes updating surveys to obtain details about targeted learners such as income, place of degree attainment, and employment status.

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Supporting Professional Learning in a Massive Open Online Course

 

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Abstract

Professional learning, combining formal and on the job learning, is important for the development and maintenance of expertise in the modern workplace. To integrate formal and informal learning, professionals have to have good self-regulatory ability. Formal learning opportunities are opening up through massive open online courses (MOOCs), providing free and flexible access to formal education for millions of learners worldwide. MOOCs present a potentially useful mechanism for supporting and enabling professional learning, allowing opportunities to link formal and informal learning. However, there is limited understanding of their effectiveness as professional learning environments. Using self-regulated learning as a theoretical base, this study investigated the learning behaviours of health professionals within Fundamentals of Clinical Trials, a MOOC offered by edX. Thirty-five semi-structured interviews were conducted and analysed to explore how the design of this MOOC supported professional learning to occur. The study highlights a mismatch between learning intentions and learning behaviour of professional learners in this course. While the learners are motivated to participate by specific role challenges, their learning effort is ultimately focused on completing course tasks and assignments. The study found little evidence of professional learners routinely relating the course content to their job role or work tasks, and little impact of the course on practice. This study adds to the overall understanding of learning in MOOCs and provides additional empirical data to a nascent research field. The findings provide an insight into how professional learning could be integrated with formal, online learning.

Keywords: MOOCs; massive open online courses; professional learning; self-regulated learning

Introduction

Professional work and learning are deeply intertwined. Where learning at work takes the form of formal, deliberate training or development it is easy to identify as 'learning'. By contrast, non-formal learning embedded in everyday work activities is more difficult to recognise as 'learning' (Eraut, 2000). Yet both forms of learning, formal and non-formal, are important for the development of different forms of expertise. Theoretical expertise may be learned through deliberate effort, while practical expertise is learned 'on the job'. Therefore the interweaving of professional practice and professional learning offers a new basis for how we think about work, education, and learning (Beckett & Hager, 2002).

Conventional forms of professional training, such as workshops or courses with alternate periods of formal instruction and practical experience, often do not fully exploit the linkages between professional practice and professional learning. This means the existing knowledge, professional and personal networks that each professional brings to their learning setting remains under-exploited (Littlejohn, Milligan, & Margaryan, 2011). The near ubiquity of computer technology provides great potential for networked learning that promotes and supports connections between learners and resources (Jones & Steeples, 2002). However, professional learning has (largely) not taken advantage of the opportunities networks afford around how people collaborate to learn, how feedback can be exploited, and the multiple ways in which people and resources can be brought together to enhance learning (Littlejohn & Margaryan, 2013).

One of the most visible forms of networked learning are massive open online courses (MOOCs): online courses aimed at open participation and access via the web and usually delivered free of charge, lowering social, cultural and geographic barriers to participation. MOOCs draw on the ubiquity of the web, spanning boundaries and bringing people with diverse experiences together. Even where courses are formal, the 'open' and online format offers a useful approach to professional learning, potentially capitalising on the inter-relationship between professional practice and learning through allowing each individual to tailor specific learning needs to their work demands. This paper describes one of the first studies examining professional learning in a MOOC. The study explores the learning behaviours of health professionals within Fundamentals Of Clinical Trials, a MOOC offered by edX. Through this research we have gained insight into how professionals learn within a MOOC environment. The study used self-regulated learning (SRL) as a theoretical lens, examining individual's learning behaviours across the three phases of SRL identified by Zimmerman (2000): forethought, performance, and self-reflection. The research questions were:

- RQ1: How do professionals prepare for learning in a MOOC? This question explores the motivations and expectations of professional learners as well as their goal setting and strategic planning during the forethought phase.

- RQ2: What learning behaviours do professionals exhibit while learning in the MOOC? This question examines the ways professional learners interact with the course materials, other learners, and members of their professional network as they learn during the performance phase.

- RQ3: How do professionals relate their MOOC learning to their professional role? This question focuses on Zimmerman's self-reflection phase, questioning the perceived impact of the MOOC on an individual's professional practice.

The paper begins with a review of relevant literature on professional learning and learning in massive open online courses. Next, the course context is described, followed by a description of the methodology adopted and the sample studied. The study findings are then presented and the implications of these findings for research and practice are discussed.

Review of Learning Literature

Many professionals operate in settings where profound social and technological changes are fundamentally changing the nature of work (Dall'Alba, 2009, p. 4). Conventional forms of professional training are losing currency, particularly where they do not address critical dimensions of professional learning important for the contemporary workplace (Littlejohn & Margaryan, 2013). First, job roles are becoming more specialized to the point that the learning required for a specific role has to be *personalized*. Conventional professional training, such as workshops and courses, is useful in allowing groups of people to reach a general level of competency. Nonetheless, these forms of training generally do not support bespoke learning. MOOCs potentially allow for personalized learning by giving professionals opportunity to align formalized learning with their practice, learning (via the network) with others who share similar and complementary experience and expertise. Their potential depends on how professionals align their personal learning goals with learning in the MOOC. Second, when work practice evolves continually, professionals constantly need to learn fresh knowledge to solve the new problems (Hager, 2004). Learning for work often blends deliberate, formalised learning with reactive, non-formal learning (Eraut, 2000). MOOCs open access to education, potentially offering a means by which professionals can continually update their knowledge. However, little is known about whether and how professionals learn in a MOOC environment and how this learning impacts upon their professional role. Third, when work roles are fluid and constantly changing, individuals continually have to draw upon existing knowledge across disciplinary or sectoral frontiers, connecting in ways that allow them to build new knowledge (Engeström, 2009). The knowledge professionals need to learn may be scientific (factual), experiential (practice based), socio-cultural or self-regulative (Tynjälä, 2008). Professionals need to be able to take greater responsibility for self-regulating their own professional learning, blending formal courses that tend to emphasise scientific knowledge, with non-formal opportunities from practice to learn experiential, socio-cultural or self-regulative knowledge.

Self-regulation is the 'self-generated thoughts, feelings and actions that are planned and cyclically adapted to the attainment of personal goals' through three phases: forethought, performance and self-reflection (Zimmerman, 2000). Within these three phases, Zimmerman identified a number of sub-processes that self-regulating learners use, with more effective learners using a broader range of sub-processes. Each individual's ability to self-regulate their learning is context dependent, influenced by these personal dispositions as well as by factors associated with the environment in which he or she is learning. Some components of self-regulation are related to personal ability, while others are aligned with context.

One critical aspect of self-regulation, and of professional learning, is the ability to integrate different types of knowledge and expertise. Professional expertise has four basic components (Tynjälä & Gijbels, 2012): *factual knowledge* which is based around conceptual or theoretical knowledge often codified in books, reports and other media sources; *experiential knowledge* which is difficult to codify and is often acquired through professional practice; *self-regulative knowledge*, focused on metacognition and 'knowing oneself'; and *sociocultural knowledge*, which is embedded in the social practices of groups and communities, providing a framework for interactions (Tynjälä & Kallio, 2009). All four types of knowledge are critical for effective working. Conventional professional development and training focuses on factual knowledge, leaving professionals to develop their experiential, self-regulative and sociocultural knowledge through on-the-job practice. A critical element of each professional's self-regulated learning is to assimilate learning of all four types of knowledge through an 'integrative pedagogy' (Tynjälä & Gijbels, 2012).

Another environment where learners must take an active role in managing their learning is a MOOC. MOOCs present a potentially useful mechanism for supporting and enabling professional learning, bringing diverse groups of learners together, united by common (or at least complementary and overlapping) learning needs. In this way, MOOCs could serve as a catalyst for the formation of heterogeneous learning communities that facilitate knowledge exchange. An underlying assumption is that learners have the skills and dispositions necessary to learn autonomously and socially within the MOOC. However, by definition, MOOCs attract a broad range of learners with diverse dispositions who differ in their ability to self-regulate their learning (Milligan, Littlejohn, & Margaryan, 2013). There is evidence that learning strategies in MOOCs are influenced not only by learners' motivation and confidence, but also by the structure of the course, the delivery environment, and the perceived value of learning (Kop, 2011). Many authors have explored the impact of self-regulated learning skills on learner behaviour in formal, online courses (see Bernacki, Aguilar, & Byrnes, 2011 for a comprehensive review). A clear link between self-regulated learning behaviours and learning success in online environments is established focusing on self-efficacy, interactions with others, and strategies for regulation. However, the strategies and behaviours needed for autonomous learning in MOOCs are not well understood (Liyanagunawardena, Adams, & Williams, 2013). This gap in knowledge is of concern, given the recent rapid growth of MOOC initiatives (Daniel, 2012) from providers such as edX, Coursera, and FutureLearn.

Context

We explored the learning behaviours of health professionals studying the Fundamentals of Clinical Trials MOOC (https://www.edX.org/course/harvard-university/hsph-hms214x/fundamentals-clinical-trials/941). The MOOC was designed by Harvard Medical School, Harvard School of Public Health, and Harvard Catalyst, The Harvard Clinical and Translational Science Center and offered through the edX initiative founded jointly between Harvard University and MIT. Our reason for selecting this MOOC was because a) the course was likely to attract a high number of participants working in the health domain, allowing us to examine how professionals learn and b) the course design was typical of the so-called ‘xMOOCs’ typified by the major MOOC providers (EdX, Coursera, Futurelearn). The MOOC provided an introduction to the scientific, statistical, and ethical aspects of clinical trials research. Each week, video lectures and course readings were presented, accompanied by a short automated assessment. To gain a certificate of completion, participants had to pass the assessments (80%) and participate in two moderated case study discussions. The course was intended for individuals interested in conducting clinical trials who had foundations in epidemiology and biostatistics and attracted a combination of medical students and medical and health professionals. Over 22,000 learners registered for the course which ran from October 2013 until February 2014.

Method

A message posted to the course website in week 4 (of 12) of the course (November 2013) invited learners to participate in the study by initially completing an online survey instrument (http://tinyurl.com/srlmq). The survey instrument was designed to establish a self-regulated learning (SRL) profile for each study participant (not used in this analysis), as well as providing demographic data for the study. Gender, age, educational background and geographic distribution of the sample reflected the overall distribution of the course cohort as reported on the HarvardX insights pages (http://harvardx.harvard.edu/harvardx-insights). Participants who completed the survey instrument were invited to volunteer for a follow-up interview. Volunteers who also identified as a healthcare professional were then invited to participate in a semi-structured interview exploring their learning within the MOOC in more detail. Interview questions were designed to explore learning behaviour according to the SRL phases and sub-processes as described by Zimmerman (2000). The interview script is available at http://tinyurl.com/plmooc-script. Thirty-five interviews (16 male and 19 female, from 23 countries) were conducted and recorded (via Skype) during December 2013 and January 2014. Interviews were transcribed and stripped of identifying information. Transcripts were analysed and a combination of pre-defined and emergent codes used to categorise the data using the NViVO software package. Ethical standards for the study were adopted in accordance with local regulations and participants were free to withdraw at any point.

Results

RQ1: How do Professionals Approach Learning in the MOOC?

Forethought is critical to a learner's participation in a course. Zimmerman (2000) describes the forethought phase as the processes that occur before efforts to learn and comprise two key components – task analysis and planning processes, and self-motivational processes. Motivation determines the amount of effort a learner will devote to learning, and his or her persistence when other priorities (e.g., work or family) compete for attention. Planning allows the learner to monitor their progress and adapt their learning as necessary. Therefore we collected data through questions focusing on motivation and goal setting.

The first interview question was 'Why did you sign up for this MOOC?' For around half the respondents (18/35: 51.4%) participation was motivated by a desire to complement or formalise existing professional knowledge. This group included those who wished to maintain expertise as well as those who recognised that their prior learning had not prepared them adequately for their current role. One respondent who had originally trained as a medical doctor had changed roles. She described the gap in her knowledge as follows: "I work in a CRO (clinical research organisation) as a project manager, so [I'm familiar with clinical trials], but I don't carry a real fundamental background in this area" (respondent 24, project manager at clinical research organisation). The course attracted learners with a range of experience, from experts to people who were new in post. These people had noted immediate gaps in their knowledge that they needed to fill. A novice had signed up because he/she needed new knowledge for her new job role: "I had recently been appointed as a pharmacist in clinical trials at the hospital I work at and of course I'd got this job but I didn't know a great deal about clinical trials" (256, pharmacist). An expert, with twelve years of experience noted an opportunity to fill gaps in knowledge: "... when I saw the syllabus of this training I was amazed because there are some things that I'm not very good at, like biostatistics etc. So there was a lot to learn for me" (373, clinical research consultant). Another group (10/35: 28.6%) focused on longer term benefits. For them the course was less about filling an immediate knowledge gap and more about unlocking future career opportunities. A respondent from India understood how the course might help her expand her role: "... a lot of emphasis is being laid on research and I need to familiarise myself with clinical trials so that I myself can do research if possible" (226, consultant, department of medicine). While most respondents related their participation closely to a current or future role challenge, only one respondent reported that they were motivated by any broader value of the course, for example in providing opportunities to interact with professionals from other countries to learn about their context: "Well because I'm a researcher so it was a nice way to ... I don't know ... see how other countries function in this field most of all and also to refresh a little bit" (280, pharmacist). A few people had more general motivations that were not linked to professional learning, citing reasons including 'fun' or general interest (4/35: 11.4%) or participating in a 'Harvard course' (3/35: 85.7%).

Moving beyond learner motivation, we asked learners about their aims and goals. Most (26/35: 74.3%) respondents described aims focused on new specific knowledge or skills they hoped to acquire; for example, "the aim was to gain knowledge about every step that is required in order to have a clinical study approved and then your drug put on the market: (78, medical doctor). Another response illustrates the learner making a link with their own practice: "my main aim is to get a basic grasp of critical concepts of clinical research, a history of different models of clinical trials designing and regulatory things that we have to abide by and the future prospect of clinical research" (128, research coordinator). Only one respondent highlighted a higher level aim focused on their broader professional practice: "I want to explore my knowledge in my professional field by gaining knowledge from this online course ... I will improve my knowledge and I will share my experiences with my colleagues and my juniors" (26, clinical data curator). Of the remainder, three articulated only vague aims based around their career, while five highlighted the attraction of gaining a certificate from Harvard.

While most respondents were readily able to summarise their aim, not all had set specific goals to guide their learning in the course. Goals are important to successful learning as they function to direct effort and define standards for successful completion (Sitzmann & Ely, 2011). When asked whether they set specific goals at the beginning of the course, 11 (11/35: 31.4%) respondents initially answered no (though most were able to articulate goals when prompted). Of the 24 who said they had set goals, the majority (17/24: 70.8%) were focused on achieving a particular level of participation in the course such as "to attend all the lectures" (22, medical epidemiologist). Some had set an additional goal to gain the course certificate, though it was recognised that the main value of the certificate was personal. Only seven respondents articulated learning goals, focused on the topic of the course. Of these, only two had specific goals: "My goal was to be very confident of my fundamentals on probability, in statistics" (295, physician) and "to understand the statistics and clinical trials and data protection" (371, psychiatrist) while the remainder articulated learning goals that were categorised as vague, typified by, "to have an in depth knowledge of this area" (152, R&D innovation projects coordinator).

RQ2: What Learning Behaviours do Professionals Exhibit while Learning in the MOOC?

As well as understanding a learner's motivations and expectations, it is useful to build up a picture of how learners actually behave as they learn within the MOOC – what tools and learning strategies they are using and how they are interacting with other learners and their professional network. The second research question was explored through a number of questions relating to sub-processes of the performance phase of SRL described by Zimmerman (2000).

Respondents were first asked about the tools and resources they used to support their learning and how they used them. A small number (5/35: 14.3%) focused only on using core course materials (videos and transcripts, and the course textbook): "I get very concentrated on the video content and the homework content and the assignments and whatever resource is needed to provide these assignments and I don't distract myself much more because ... of the time constraints" (152, R&D innovation projects coordinator). All other respondents made use of the additional recommended resources, particularly the course eBook, and Wikipedia resources referred to during the course. All of this group also made use of other resources outside the course - the internet or their own books and pre-existing notes, however for most (21/30: 70%), their use of resources beyond course materials was minimal and irregular (not routine). Only a small number (9/35: 25.7%) of respondents described more extensive or specific strategies for augmenting their learning with this small group citing one or more specific external sources as forming a significant part of their learning on the course. Six respondents used Google Scholar or PubMed to explore primary scientific literature, while four made reference to YouTube as a source of alternative explanations, including one respondent who described how they integrated information from a range of sources:

> ... UCLA has a good statistics site, there are scholarly articles, Google Scholar has a number of things. Wikipedia is there, ... I go to YouTube and watch videos, like sometimes ... in my class I have not understood [a specific topic], so I go to YouTube and I try to see a few more videos on it and then I combine all these things, collate my understanding and come back now I have understood it. (295, physician)

Even among this group, the data indicates that exploring beyond the core course materials was not the norm.

We were interested to know whether study participants created their own resources while learning in the MOOC, as SRL research in online learning contexts has uncovered a link between students with sophisticated learning strategies (such as taking structured notes) and greater academic achievement (Kauffman, 2004). Almost half the respondents (16/35: 45.7%) described making notes of some kind, either paper or electronic. Sometimes notes were integrated with the course materials: Seven respondents described how they downloaded and organised course materials and therefore had created their own resource library of course materials, while a further three respondents described making physical (paper) copies of course resources which they then annotated with their own notes. It is interesting to note that none of the respondents described maintaining a blog or sharing via twitter: Any materials created were solely for their own use. One study participant had shared resources through a Facebook group set up by some learners. Eleven respondents (11/35: 31.4%) stated that they had not created any materials.

So far, the study has explored different ways in which the respondents have interacted with the course on their own. However learning is a social process and the MOOC includes opportunities for learners to communicate within the course forums. Even more significantly, as professionals, these learners have ready-made networks of colleagues with whom they may choose to discuss the course concepts. SRL research highlights the importance of interaction as a learning strategy adopted by successful learners in online contexts (Cho & Kim, 2013), while workplace peers are recognised as a valuable source of learning support (Eraut, 2007). The next series of questions were designed to explore how respondents had interacted with other learners, with tutors, and with other members of their professional network. Within the course, the main mechanism for communication was the course discussion forum. Almost half (17/35: 48.6%) of the respondents interacted in the discussion forum, either to discuss the course or share links they had found. The discussion forum received mixed responses. Some respondents were positive about the forum, recognising its value as a source of learning: “there were some candidates that were actually wonderful at giving explanations and in such detail and depth ... some of them are so, so good” (256, pharmacist). Another respondent, who used the forum daily, made a similar assertion:

> My experience with the MOOC so far is equal learning, if not more, happens in the discussion forum. It is a great place and I make it a point that I visit the discussion board every single day, read through most of the posts which I can and try and participate/share my views as well. It’s an amazing place. (295, physician)

However, negative attitudes were more common, with frustration at poor technical functionality and unanswered questions:

> No one was helpful. Most of them didn’t even understand what I meant at all, that was funny, I have tried 2 or 3 times to try and explain my problem and they couldn’t understand me at all, I gave up and I really honestly don’t have the time to spend so much time on the discussion board. (72, surgeon)

A small number of respondents (7/35: 20%) read the discussion forums but made a conscious decision not to contribute, choosing instead to 'lurk'. For some, this behaviour was motivated by time pressures: "But I go in the discussions and usually I find my answer within the discussions between the students. I don't get involved in the discussions because I know that time is limited" (152, R&D innovation projects coordinator) while for others, lack of confidence was a barrier. A native Spanish speaker (forum discussions were in English) described his interaction in the forums as follows: "Not much really. I've seen this is more a personal limitation than course limitation. I don't feel very comfortable interacting just texting and expecting an answer" (249, neurologist).

As professionals, the learners in the study should already have networks of colleagues with whom they might discuss the course. This group can be particularly useful in translating the course materials into knowledge related to current practice. Colleagues provide local expertise that can help to personalise learning and, for non-English speakers, present an opportunity to think and discuss in one's own language. We were interested in the extent to which learners on the course discussed the content with their external networks. Around half of the respondents (17/35: 48.6%) did speak to people outside the course, mainly to colleagues, while two respondents whose partners were also healthcare professionals also discussed with their spouses. When asked what they discussed, responses fell into two categories (some respondents mentioned both). The first category included those (13/35: 37.1%) who passed on new knowledge from the course to others in their network: "I downloaded some videos and I sent them to some colleagues who are interested in clinical trials" (358, nurse) or who discussed the course content:

> Yeah I have spoken about the course with my fellow colleagues who are working on the clinical trials with me in the capacity of coordinator … have a good understanding of a critical concept and the history behind the research and different terms that affects this type of field, it's definitely going to help in my work and in the long run as well. (128, research coordinator)

A second group (8/35: 22.9%) looked for support from their colleagues. For example one respondent discussed aspects they were unsure of with a colleague: "I [asked] another colleague of mine about some technical points in the course content, that's not related to my background" (28, physiotherapist) while another found new resources through friends: "I have friends who already have Masters with statistics, so they sent me videos to help me" (366, lecturer). Interactions with external networks that were reported appeared isolated, with no respondents reporting that they regularly or routinely discussed the course with their network, though there was one respondent who had signed up for the course with friends and colleagues whose contact was more regular: "normally when any of us have any difficulty we contact each other and share these, like in life or in a direct way" (249, neurologist).

RQ3: How do Professionals Relate their MOOC Learning to their Professional Role?

The lasting value of professional learning comes when it can be applied back into practice. This study sought to explore how learners perceived the relation of course and practice by investigating the self-reflection behaviour of respondents. Learners were first asked whether they expected to integrate what they had learned into their professional practice. To this question, all respondents gave a positive response. Of course it should be highlighted that the interviews were conducted around halfway through the course; perhaps those who found little or no value in the course had already withdrawn. The majority (23/35: 65.7%) saw the course as having a broad impact on their role, either immediately, "Well it gives me a better understanding of why I do what I do. ... I understand why I have to submit my protocol or a complete or total submission to authorities, how a protocol has been developed" (255, clinical trials project manager), or in the future:

> I would like to move my career more in the research field. ... I work at an academic teaching and research institution ... and I know they're going to be building a research building soon, so I would like to move my career in that direction. (334, clinical pharmacist)

A smaller number (12/35: 34.3%) were able to give more specific examples of how they expected to use their new knowledge immediately as the following example illustrates:

> ... right now we're doing some ethical committee issues and I saw those documents from United Kingdom and it's interesting because here in [my country] it's a little bit different, procedures and so on. ... it's also useful because if you have to collaborate with other countries you have to understand how [they] function, you have to adapt yourself. (280, pharmacist)

A similar question asked respondents to reflect on how their practice had changed as a result of the course. More than half (19/35: 54.3%) felt the course had had an immediate impact on their practice. These respondents reported a range of general benefits: that the course had given them a new perspective, had made them assured, or had helped them bring a greater criticality to their practice. One respondent described her increased confidence: "I know why and why not ...you have an overview, I cannot say I apply everything in my day to day work, but the fact that you feel more confident, for me, it helps a lot" (255, clinical trials project manager). Another described a new perspective: "I guess it has changed in the way that one looks at some of the problems that you encounter at work and the solutions" (394, medical laboratory scientist). Even by half way through the course, some respondents were able to report direct changes to their practice: "It is much, much better, I could address all of the challenges much better and make better decisions and actually I participate with this CRO in developing the protocol and the study documents and everything"(152, R&D innovation projects coordinator). As the course was still ongoing, some (11/35: 31.4%) respondents felt that although they expected their practice to change, it had not done so yet. There was also some variation in what might constitute a practice change: While some participants described bringing new knowledge to bear on their decision making, others implied that while this might be so, constraints on their working practice meant that their actual practice would not change.

As well as understanding the link between the course and individual professional practice, the study sought to explore how learners valued the course. Respondents were asked whether they had talked to members of their professional network about the value (as opposed to the content) of the course or reflected on its value. Three respondents had talked to their manager about the course, as illustrated by the following quote: "We discussed already before I started whether it would be something that would be beneficial for my work" (143, epidemiologist). Only six respondents reported making any informal or formal record of their learning. These were primarily personal notes made alongside learning materials, but two respondents reported recording their learning formally for professional development; for example: "We have sort of an academic review that goes on every 6 months or so of our performance and this would be one of those things that I would put on that list of accomplishments" (360, otolaryngology resident). While not reflection, a large group (21/35: 60%) had clearly seen value in the course, because they reported that they had recommended it to others. The enthusiasm of one respondent who encouraged a senior colleague to participate is clear: "I told him about the course he got very interested and he is in the process of joining it ... I just told him it's fantastic and you should not miss this opportunity and he is going to join" (226, consultant in department of medicine).

Discussion and Conclusion

This study surfaces some of the benefits and issues with MOOCs as a form of professional learning.

First, whether and how professionals align their professional goals with the aims of the course were examined through the research question, 'How do professionals prepare for learning in a MOOC?' Many of the professionals articulated their intention to align the MOOC with immediate or future (perceived) professional learning needs. However, their performance in the course focused on viewing and reading content and completing assessments in order to gain a certificate at the conclusion of the course. This switch in participants' focus from learning knowledge for specific work tasks to gaining a certificate highlights the mismatch between the type of learning for work inherent in informal, professional learning and formal for-credit learning. There was no evidence of professionals personalising course goals by linking theory to their professional practice.

The learning behaviours of study participants were explored in detail through the second research question: 'What learning behaviours do professionals exhibit while learning in the MOOC?' Professionals tended to work on their own, reading and viewing pre-prescribed material. Study participants were focused on the core course materials. While most did also access additional resources, only a minority did this to any significant extent. Focusing effort on core course materials and activities is an effective strategy for achieving participation goals, but can result in a diminished learning experience as non-core aspects of the course, such as the exchange of ideas and experience that may occur in the discussion forum are neglected. There was little exchange of ideas and experience with the (massive numbers) of other participants and little evidence that learners were drawing on each other's experience. In this respect, the advantages afforded by networked learning seem to have been under-exploited. Around half of the study participants reported discussing course content with their external networks, to seek support or to explore ideas with trusted colleagues or relations. However as with accessing additional content, discussing the course content with external networks did not appear to be routine but rather driven by opportunity (chance meetings) or necessity (asking for support that was not available from the course tutors). These findings suggest that learners on this course are missing the opportunity to draw on the expertise of others participating in the MOOC. Professional learners bring a wealth of experience to their learning. Yet this experience remained (largely) untapped with little opportunity for learners to share their experience and build on their existing knowledge.

The third research question 'How do professionals relate their MOOC learning to their professional role?' explored the link between theory (in the MOOC) and practice (on-the-job). However the course did not promote or encourage the integration of the theory learned during the course with on-the-job practice. There were few examples of professionals linking the MOOC with their practice and almost no instances of practice change through participation in the course. Professionals placed little value on reflection on how the knowledge they learned on the course might impact their practice. A minority reflected on the value of the course with colleagues or individually. There were limited opportunities for learners to reflect on the knowledge gained from the course and how it may be embedded into their work practice before the end of the course. These findings illustrate the limitations of this type of course in improving professional practice. Yet the majority of participants reported they *had* learned about the ethics and statistical methods of clinical trials. Overall, the course was viewed positively by all respondents. Almost all professionals were active proponents for the course and there was evidence of extensive recommendation through external networks.

The use of a traditional course format for this MOOC appears to have limited its value as professional learning. Boud and Hager (2012) have highlighted the failings of professional development approaches that focus on certification and measurement, calling instead for professional learning to focus on individual needs, tightly integrated with work practice. To support professional learning, a MOOC could be designed along the principles of integrative pedagogy (Tynjälä & Kallio, 2009) that explicitly sought to combine theory and practice, and to take advantage of the key attributes of professional learners. Professionals have precise learning needs, based on their role, background and motivations. A professional learning MOOC could encourage professional learners to take ownership of their learning by asking them to set personal goals, or at least personalise course goals that link theory to their own practice. The MOOC design could also exploit the existing knowledge of its professional learners as a core course resource. Professional learners bring a wealth of experience to their learning. Designing tasks which capitalise on this by encouraging the learners to build on existing knowledge and share their experience can enrich the learning experience for all by exposing learners to real world experience and new practices. Engaging with real world examples can be motivating and provides learners with evidence that they can use for their own personal development. Finally, a professional learning MOOC could support professional learners to reflect on the knowledge gained from the course and how it may be embedded into their work practice before the end of the course.

The findings presented here represent one aspect of a wider study exploring how design of MOOCs can foster professional learning. While this research contributes new empirical data collected there are some constraints. The key limitation is that the present study is based on data collected from a single course. While we are confident that our findings are broadly generalizable (it is likely learners in similarly designed MOOCs would display comparable behaviours), similar studies conducted in different contexts would strengthen these findings. The next phase of this study will explore the same research questions in a different MOOC context. In addition, the instruments developed for this study are publicly available for other researchers to repeat and refine our analysis in different courses. The qualitative nature of the data in this study also limits the conclusions that can be drawn from this work, but it is important to collect this type of data to enrich our understanding of learner behaviour in MOOCs. Although not presented here, our own study also collected quantitative data and our overall analysis will combine both types of data. A third limitation is the absence of any measure of successful professional learning in this study. Immediate impact on practice is likely to be limited, therefore longitudinal, ethnographic methods could provide greater insights.

Acknowledgements

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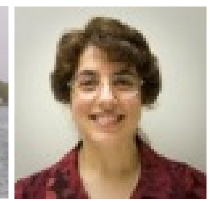
Towards an Integration of Text and Graph Clustering Methods as a Lens for Studying Social Interaction in MOOCs







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Abstract

In this paper, we describe a novel methodology, grounded in techniques from the field of machine learning, for modeling emerging social structure as it develops in threaded discussion forums, with an eye towards application in the threaded discussions of massive open online courses (MOOCs). This modeling approach integrates two simpler, well established prior techniques, namely one related to social network structure and another related to thematic structure of text. As an illustrative application of the integrated technique's use and utility, we use it as a lens for exploring student dropout behavior in three different MOOCs. In particular, we use the model to identify twenty emerging subcommunities within the threaded discussions of each of the three MOOCs. We then use a survival model to measure the impact of participation in identified subcommunities on attrition along the way for students who have participated in the course discussion forums of the three courses. In each of three MOOCs we find evidence that participation in two to four subcommunities out of the twenty is associated with significantly higher or lower dropout rates than average. A qualitative post-hoc analysis illustrates how the learned models can be used as a lens for understanding the values and focus of discussions within the subcommunities, and in the illustrative example to think about the association between those and detected higher or lower dropout rates than average in the three courses. Our qualitative analysis demonstrates that the patterns that emerge make sense: It associates evidence of stronger expressed motivation to actively participate in the course as well as evidence of stronger cognitive engagement with the material in subcommunities associated with lower attrition, and the opposite in subcommunities associated with higher attrition.

We conclude with a discussion of ways the modeling approach might be applied, along with caveats from limitations, and directions for future work.

Introduction

The contribution of this paper is an exploration into a new methodology that provides a view into the evolving social structure within threaded discussions, with an application to analysis of emergent social structure in massive open online courses (MOOCs). In the current generation of MOOCs, only a small percentage of students participate actively in the provided discussion forums (Yang et al., 2013; Rosé et al., 2014). However, social support exchanged through online discussions has been identified as a significant factor leading to decreased attrition in other types of online communities (e.g., Wang, Kraut, & Levine, 2012). Thus, a reasonable working hypothesis is that if we can understand better how the affordances for social interaction in MOOCs are functioning currently, we may be able to obtain insights into ways in which we can design more socially conducive MOOCs that will draw in a larger proportion of students, provide them with needed social support, and ultimately reduce attrition. In this paper we focus on the first step down this path, namely developing a methodology that can be used to gain a bird's eye view of the emerging social structure in threaded discussion. As such, this is a methods paper that describes a modeling approach, and illustrates its application with a problem that is of interest to the online and distance education community.

Current research on attrition in MOOCs (Koller et al., 2013; Jordan, 2013) has focused heavily on summative measures rather than on the question of how to create a more socially conducive environment. Some prior work has used clustering techniques applied to representations of clickstream data to identify student practices associated with levels of engagement or disengagement in the course (Kizilcec, Piech, & Schneider, 2013). Our work instead focuses on social interaction within the MOOC exclusively. In particular, the motivation is that understanding better the factors involved in the struggles students encounter and reflect to one another along the way can lead to design insights for the next generation of more socially supportive MOOCs (Yang et al., 2013; Rosé et al., 2014). As large longitudinal datasets from online behavior in MOOCs are becoming easier to obtain, a new wave of work modeling social emergence (Sawyer, 2005) has the potential to yield valuable insights, grounded in analysis of data from learning communities as they grow and change over time. Powerful statistical frameworks from recent work in probabilistic graphical models (Koller & Friedman, 2009) provide the foundation for a proposed new family of models of social emergence (Sawyer, 2005). This paper particularly focuses on integration of two well established prior techniques within this space, namely one related to social network structure (Airoldi et al., 2008) and another related to thematic structure of text (Blei et al., 2003).

From a technical perspective, we describe how the novel exploratory machine learning modeling approach, described in greater technical detail in our prior work (Kumar et al., 2014), is able to identify emerging social structure in threaded discussions. Our earlier account of the approach focused on the technical details of the modeling technology and an evaluation of its scalability in an online cancer support community and an online Q&A site for software engineers. This paper instead focuses on a methodology for using the approach in the context of research on MOOCs.

In the remainder of this paper, we begin by describing our methodology in qualitative terms meant to be accessible to researchers in online education and learning analytics. Next, we present a quantitative analysis that demonstrates that the detected subcommunity structure provided by the learned models predicts dropout along the way across three different Coursera MOOCs. Specifically, we describe how this modeling approach provides social variables associated with emerging subcommunities that students participate in within a MOOC's threaded discussion forums. We evaluate the predictive validity of these social variables in a survival analysis. We then interpret the detected subcommunity structure in terms of the interests and focus of the discussions highlighted by the model's representation. We conclude with a discussion of limitations and directions for future research, including proposed extensions for modeling emerging community structure in cMOOCs (Siemens, 2005; Smith & Eng, 2013).

Method

Data

In preparation for a partnership with an instructor team for a Coursera MOOC that was launched in fall of 2013, we were given permission by Coursera to extract the discussion data from and study a small number of courses. Altogether, the dataset used in this paper consists of three courses: one social science course, "Accountable Talk™: Conversation that works", offered in October 2013, which has 1,146 active users (active users refer to those who post at least one post in a course forum) and 5,107 forum posts; one literature course, "Fantasy and Science Fiction: the human mind, our modern world", offered in June 2013, which has 771 active users who have posted 6,520 posts in the course forum; and one programming course, "Learn to Program: The Fundamentals", offered in August 2013, which has 3,590 active users and 24,963 forum posts. All three courses are officially seven weeks long. Each course has seven week specific subforums and a separate general subforum for more general discussion about the course. Our analysis is limited to behavior within the discussion forums. We will refer to the three data sets below as Accountable Talk, Fantasy, and Python respectively.

Modeling Emerging Subcommunities

Model overview.

The aim of our work is to identify the emerging social structure in MOOC threaded discussions, which can be thought of as being composed of bonds between students, which begin to form as students interact with one another in the discussion forums provided as part of many xMOOCs (e.g., MOOCs provided by Coursera, EdX, or Udacity). The structure of cMOOCs (Siemens, 2005; Smith & Eng, 2013) is more complex, and we address in the conclusion how the approach may be extended for such environments.

The unique developmental history of MOOCs creates challenges that can only be met by leveraging insights into the inner-workings of the social interaction taking place within those contexts. In particular, rather than evolving gradually as better understood forms of online communities, MOOCs spring up overnight and then expand in waves as new cohorts of students arrive from week to week to begin the course. Students may begin to form weak bonds with some other students when they join, however, massive attrition may create challenges as members who have begun to form bonds with fellow students soon find their virtual cohort dwindling.

Within these environments, students are free to pick and choose opportunities to interact with one another. As students move from subforum to subforum, they may take on a variety of stances as they interact with alternative subsets of students in discussions related to different interests, goals, and concerns. From the structure of the discussion forums, it is possible to construct a social network graph based on the post-reply-comment structure within threads. This network structure provides one view of a student's social participation within a MOOC, which may reflect something of the values and goals of that student. A complementary view is provided by the text uttered by the students within those discussions. In our modeling approach, we bring both of these sources of insight together into one jointly estimated integrated framework with the goal of modeling the ways in which the linguistic choices made by students within a discussion reflect the specific stances they take on depending upon who they are interacting with, and therefore which subcommunities are most salient for them at that time.

Just as Bakhtin argues that each conversation is composed of echoes of previous conversations (Bakhtin, 1981), we consider each thread within a discussion forum to be associated with a mixture of subcommunities whose interests and values are represented within that discussion. This mixture is represented by a statistical distribution. Whenever two or more users interact in a thread, they each do so assuming a particular manner of participation that contributes to that mixture of subcommunities via the practices that are displayed in their discussion behavior. Within each thread t, each user u is considered to have a probabilistic association with multiple subcommunities $c_1 \ldots c_n$ based on who he spends time talking with and the way he talks.

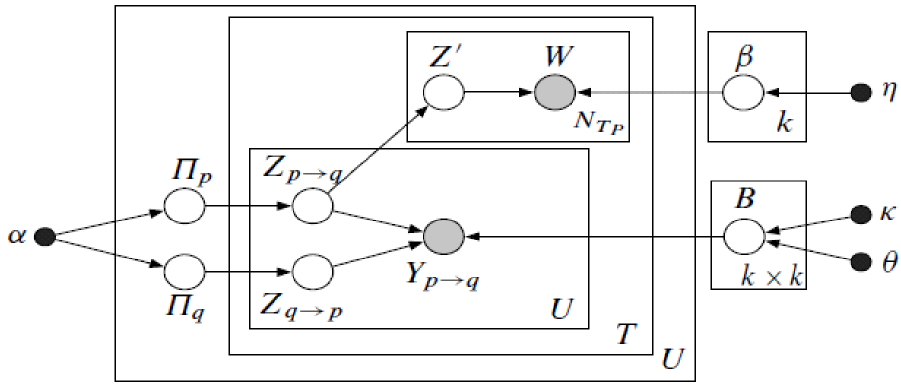

Figure 1. Graphical representation of the integrated LDA-MMSB model.

More technical readers may refer to the graphical representation of the model in plate notation in Figure 1. With reference to this representation we can state more formally as represented within the inner U plate that for each pair of users within a thread, which we may refer to as user p and user q, the distribution of subcommunities drawn for user p that reflects p addressing q is represented in the plate notation as $Z_{p\text{->}q}$, and likewise the distribution drawn for q is represented as $Z_{q\text{->}p}$. In addition to each thread specific distribution of subcommunity associations, users each have an overall distribution that represents their average tendency across all of the threads they have participated in. This is represented within the plate notation as Π_p and Π_q. This enables the model to prefer some consistency of user behavior across threads. The influence users p and q exert on one another's behavior arises from the MMSB portion of the model, which comprises a dirichlet prior (i.e., α, initialized with an assumed number of topics), from which are drawn the prior probability distribution over subcommunities associated with each user (i.e., Π_p and Π_q), and the inner U plate already described. As represented within the T plate, the LDA portion of the model reflects $Z_{p\text{->}q}$ as a mixture of word distributions, where each Z' represents a word distribution reflecting that of users when they are speaking as members of the subcommunity associated with Z'. A more extensive discussion of the technical details related to the model along with its parallelized approximate inference approach are published separately (Kumar et al., 2014).

Reflecting on the model from a conceptual standpoint, consistent with theories of social emergence (Sawyer, 2005), it is important to note that influence works both top-down, from the norms of the group to the behavior of the students within the group, and bottom-up, from the behavior of the student to the emerging norms of the group within discussions. Specifically, when users talk together on a thread, each user exerts some influence on the distribution of subcommunities whose values and goals are ultimately reflected in that conversation. However, each user is interacting with and responding to the other users on the thread. As a result, the set of users cumulatively exert some influence over the stance taken by each participant within the discussion. Thus, within a specific context, the distribution of subcommunities reflected in a participating user's behavior will be related both to the user's own tendencies and also to the tendencies of the other participants in that discussion. More formally, the cumulative reflected association of subcommunities within a thread t will emerge from the interaction of the set of users $u_1 \ldots u_n$ who are participating on t. And for each user u on thread t, his behavior on that thread will reflect each subcommunity c to the extent that it is associated with that user's own stance within that thread t. Because of this two way influence, it is reasonable to consider that subcommunity structure arises both from the pattern of connections embedded within the network constructed from the threaded reply structure and from the behaviors reflected through the text contributed within that structure. From a technical perspective, the interests and values of subcommunity c are reflected through an associated word distribution computed from the set of texts uttered by participants in subcommunity c. But they are also reflected through an association between nodes within the social network graph and subcommunity c. Thus, the representation of latent subcommunities $c_1 \ldots c_n$ mediates the network and the text.

Our model formulation integrates these two complementary views of subcommunity structure in one jointly estimated probabilistic model. This two-way influence may be modeled within this probabilistic framework through the iterative manner in which the model is estimated, which gives it a representational advantage over earlier multi-agent approaches to modeling social emergence (Hedtröm, 2005). In particular, as reflected in the structure of the plate notation, the model is estimated over the whole data set, but it is done by iterating over threads. On each thread iteration, the estimation algorithm iterates over the pairs of users who participate on the thread. And for each pair of users, it alternates between holding the LDA portion of the model constant while estimating the MMSB portion, and then holding the estimated MMSB portion constant while estimating the LDA portion.

The probabilistic formulation also has another advantage from a representation standpoint. In our model, a separate link structure is constructed for each thread. However, since each thread is associated with a distribution of subcommunities, and each subcommunity is associated with multiple threads, the text and network structures are conceptually linked. Most importantly, this probabilistic formulation enables us to represent the fact that participants reflect their connection to different subcommunities at different times depending on who they are talking with and what they are talking about. This novel approach contrasts with existing techniques built on a simple aggregation of reply networks into a single graph and user text across subforums into a single document per user and a hard partitioning of the network structure such that each user is treated as belonging only to one partition (e.g., Karypis & Kumar, 1995). This simplistic approach makes an invalid assumption about consistency of user behavior and can thus cause a severe loss of information in the resulting model, as demonstrated in our earlier work (Kumar et al., 2014).

Model reflections.

Our modeling approach integrates two types of probabilistic graphical models. First, in order to obtain a soft partitioning of the social network of the discussion forums, we used a mixed membership stochastic blockmodel (MMSB) (Airoldi et al., 2008). The advantage of MMSB over other graph partitioning methods is that it does not force assignment of students solely to one subcommunity. The model can track the way students move between subcommunities during their participation.

We made several extensions to the basic MMSB model. First, while the original model could only accommodate binary links that signal either that a pair of participants have interacted or not, we were able to make the representation of connections between nodes more nuanced by enabling them to be counts rather than strictly binary. Thus, the frequency of interaction can be taken into account. Secondly, we have linked the community structure that is discovered by the model with a probabilistic topic model, so that for each person a distribution of identified communicative themes is estimated that mirrors the distribution across subcommunities. By integrating these two modeling approaches so that the representations learned by each are pressured to mirror one another, we are able to learn structure within the text portion of the model that helps identify the characteristics of within-subcommunity communication that distinguish various subcommunities from one another. A well known approach is Latent Dirichlet Allocation (LDA) (Blei et al., 2003), which is a generative model and is effective for uncovering the thematic structure of a document collection.

LDA works by associating words together within a latent word class that frequently occur together within the same document. The learned structure in LDA is more complex than traditional latent class models, where the latent structure is a probabilistic assignment of each whole data point to a single latent class (Collins and Lanza, 2010). An additional layer of structure is included in an LDA model such that words within documents are probabilistically assigned to latent classes in such a way that data points can be viewed as mixtures of latent classes. By allowing the representation of documents as arbitrary mixtures of latent word classes, it is possible then to keep the number of latent classes down to a manageable size while still capturing the flexible way themes can be blended within individual documents.

Modeling Attrition

In order to evaluate the impact of social factors on continued participation within the MOOC context, we used a survival model, as in prior work modeling attrition over time (Wang, Kraut, & Levine, 2012; Yang et al., 2013). Survival analysis (Skrondal & Rabe-

Hesketh, 2004) is known to provide less biased estimates than simpler techniques (e.g., standard least squares linear regression) that do not take into account the potentially truncated nature of time-to-event data (e.g., users who had not yet left the community at the time of the analysis but might at some point subsequently). From a more technical perspective, a survival model is a form of proportional odds logistic regression, where a prediction about the likelihood of a failure occurring is made at each time point based on the presence of some set of predictors. The estimated weights on the predictors are referred to as hazard ratios. The hazard ratio of a predictor indicates how the relative likelihood of the failure occurring increases or decreases with an increase or decrease in the associated predictor.

Results

Quantitative Analysis

Identifying subcommunity structure as it emerges is interesting for a variety of reasons outlined earlier in this article. As just one example of its possible use, in this quantitative analysis we specifically illustrate how our integrated modeling framework can be used to measure the impact of subcommunity participation on attrition using a survival analysis. This enables us to validate the importance of the identified structure in an objective measure that is known to be important in this MOOC context.

As discussed above, we apply our modeling framework to discussion data from each of three different Coursera MOOCs, namely Accountable Talk, Fantasy, and Python. An important parameter that must be set prior to application of the modeling framework is the number of subcommunities to identify. In this set of experiments, we set the number to twenty for each MOOC based on intuition in order to enable the models to identify a diverse set of subcommunities reflecting different compositions in terms of content focus, participation goals, and time of initiating active participation. The trained model identifies a distribution of subcommunity participation scores across the twenty subcommunities for each student on each thread. Thus we are able to construct a subcommunity distribution for each student for each week of active participation in the discussion forums by averaging the subcommunity distributions for that student on each thread that student participated in that week. In the qualitative analysis we will interpret these variables in terms of the associated thematic structure via the text portion of the model. Thus, for consistency, we refer to these twenty variables as $Topic_1$...$Topic_{20}$. Note that the meaning of each of these topic variables is specific to the MOOC data set the model was estimated on.

We assess the impact of subcommunity participation on attrition using a survival model, specified as follows.

Dependent variable.

Drop: We treat commitment to the course as a success measure. Thus, the binary dependent variable is treated as having a value of 1, indicating failure, for a time point if that week was the last week in which a student participated in the course according to the data we have, which for the three MOOCs we discuss in this paper only includes the forum data. For all other time points, the variable is treated as having a value of 0.

Independent variables.

$Topic_1$...$Topic_{20}$: The numeric value of each topic variable represents the percentage of time during the time point (i.e., week of active participation) the student is identified by the model as participating in the associated subcommunity.

For each student in each MOOC we construct one observation for each week of their active participation. Weeks of no discussion participation were treated as missing data. The values of the independent variables were standardized with mean 0 and standard deviation 1 prior to computation of the survival analysis in order to make the hazard ratios interpretable. The survival models were estimated using the STATA statistical analysis package (Skrondal & Rabe-Hesketh, 2004), assuming a Weibull distribution. For each independent variable, a hazard ratio is estimated along with its statistical significance. The hazard ratio indicates how likelihood of dropping out at the next time point varies as the associated independent variable varies.

If subcommunity structure had a random association with attrition, we might expect one subcommunity variable to show up as significant in the analysis by chance. However, in our analysis, across the three courses, a minimum of two and a maximum of four were determined to be significant, which supports the assertion that subcommunity structure has a non-random association with attrition in this data. Hazard ratios for subcommunity topics identified to have a significant association with attrition over time in the survival model for the Fantasy course, the Accountable Talk course, and the Python course are displayed in Tables 1-3 respectively. For these analyses we removed the variables that corresponded to topics that did not have a significant effect in the model. For each subcommunity topic identified as associated with significantly higher or lower attrition, the associated effect was between 5% and 12%. The strongest effects were seen in the Fantasy course.

A hazard ratio greater than 1 signifies that higher than average participation in the associated subcommunity is predictive of higher than average dropout at the next time point. In particular, by subtracting 1 from the hazard ratio, the result indicates what percentage more likely to drop out at the next time point a participant is estimated to be if the value of the associated independent variable is 1 standard deviation higher than average. For example, a hazard ratio of 2 indicates a doubling of probability. As illustrated in Table 1, the four identified subcommunity topics have hazard ratios of 1.07, 1.12, 1.06, and 1.07 respectively, which correspond to a 7%, 12%, 6%, and 7%

higher probability of dropout than average for students participating in the associated subcommunities with a standard deviation higher than average intensity. Table 3 also presents two subcommunity topics associated with higher than average attrition.

A hazard ratio between 0 and 1 signifies that higher than average participation in the associated subcommunity is predictive of lower than average dropout at the next time point. In particular, if the hazard ratio is .3, then a participant is 70% less likely to drop out at the next time point if the value of the associated independent variable is 1 standard deviation higher than average for that student. As illustrated in Table 2, the two identified subcommunities have hazard ratios of .93, which indicates a 7% lower probability of dropout than average for students participating in the associated subcommunities with a standard deviation higher than average intensity. Table 3 also presents two subcommunity topics associated with lower than average attrition.

Survival curves that illustrate probability of dropout over time within the three courses as a visual interpretation of these hazard ratios is displayed in Figure 2. Again we see the most dramatic effect in the Fantasy MOOC.

Table 1

Hazard Ratios for Four Different Subcommunity Topics in the Fantasy Course

Independent variable	Hazard ratio	Standard error	P value
Topic5	1.07	.04	P < .05
Topic8	1.12	.05	P < .01
Topic11	1.06	.03	P < .05
Topic13	1.07	.03	P < .05

Note. Each is associated with higher than average attrition, which can be observed in that the hazard ratios are all greater than 1.

Table 2

Hazard Ratios for Two Different Subcommunity Topics in the Accountable Talk Course

Independent variable	Hazard ratio	Standard rrror	P value
Topic8	.93	.03	P < .05
Topic12	.93	.03	P < .05

Note. Each is associated with lower than average attrition, which can be observed in that the hazard ratios are all less than 1.

Table 3

Hazard Ratios for Four Different Subcommunity Topics in the Python Course

Independent variable	Hazard ratio	Standard error	P value
Topic9	1.06	.01	P < .01
Topic13	.95	.02	P < .05
Topic17	1.09	.01	P < .01
Topic18	.95	.02	P < .01

Note. Two are associated with higher than average attrition, and two are associated with lower than average attrition.

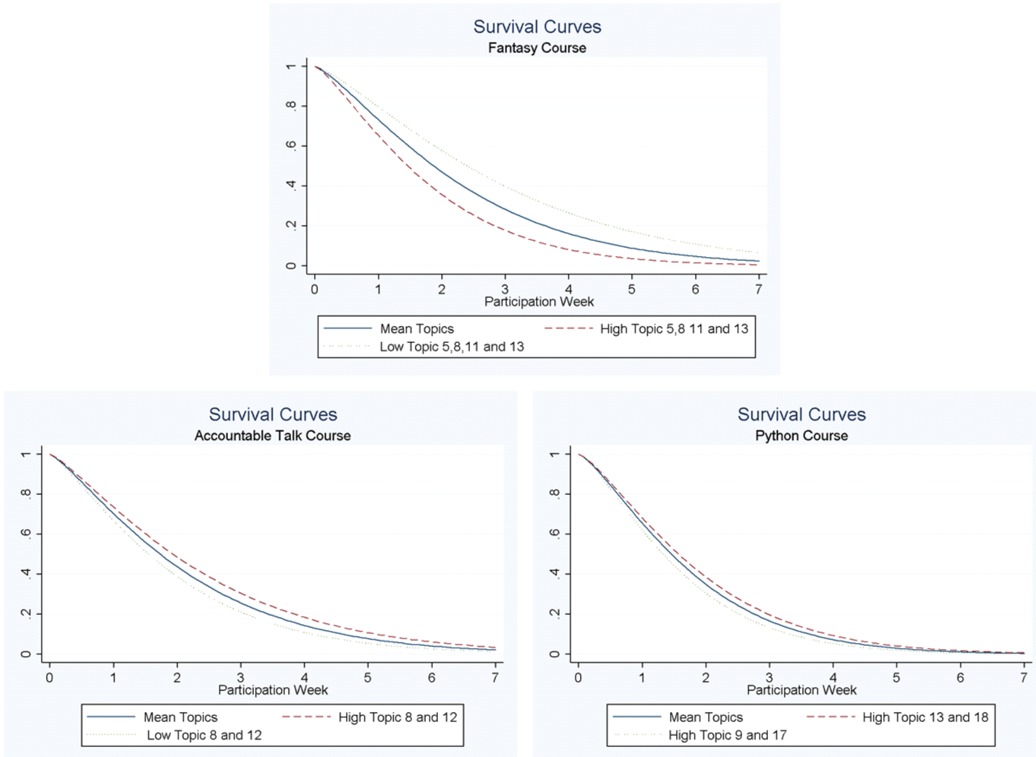

Figure 2. Survival curves for significant topics in three MOOCs.

Qualitative Analysis

In our qualitative analysis we compare topics that predict more or less attrition across MOOCs in order to demonstrate that the findings have some generality. We discuss here in detail all of the topics that were associated with significant effects on attrition in the survival models. One interesting finding is that we see consistency in the nature of topics that predicted more or less attrition across the three MOOCs.

In our analysis, we refer to student-weeks because for each student, for each week of their active participation in the discussion forum, we have one observational vector that we used in our survival analysis. The text associated with that student-week contains all of the messages posted by that student during that week. We will use our integrated model to identify themes in these student-weeks by examining the student-weeks that have high scores for the topics that showed significantly higher or lower than average attrition in the quantitative analysis.

When an LDA model is trained, the most visible output that represents that trained model is a set of word distributions, one associated with each topic. That distribution specifies a probabilistic association between each word in the vocabulary of the model and the associated topic. Top ranking words are most characteristic of the topic, and lowest ranking words are hardly representative of the topic at all. Typically when LDA models are used in research such as presented in this paper, a table is offered that lists associations between topics and top ranking words, sometimes dropping words from the list that don't form a coherent set in connection with the other top ranking words. The set of words is then used to identify a theme. In our methodology, we did not interpret the word lists out of the context of the textual data that was used to induce them. Instead, we used the model to retrieve messages that fit each of the identified topics using a maximum likelihood measure and then assigned an interpretation to each topic based on the association between topics and texts rather than directly to the word lists. Word lists on their own can be misleading, especially with an integrated model like our own where a student may get a high score for a topic within a week more because of who he was talking to than for what he was saying. We will see that at best, the lists of top ranking words bore an indirect connection with the texts in top ranking student-weeks. However, we do see that the texts themselves that were associated with top ranking student-weeks were nevertheless thematically coherent.

Because LDA is an unsupervised language processing technique, it would not be reasonable to expect that the identified themes would exactly match human intuition about organization of topic themes, and yet as a technique that models word co-occurrence associations, it can be expected to identify some things that would make sense as thematically associated. In this light, we examine sets of posts that the model identifies as strongly associated with each of the topics identified as predicting significantly more or less drop out in the survival analysis, and then for each one, identify a coherent theme. Apart from the insights we gain about reasons for attrition from the qualitative analysis, what we learn at a methodological level is that this new integrated model identifies coherent themes in the data, in the spirit of what is intended for LDA, and yet the themes may not be represented strictly in word co-occurrences.

Fantasy and Science Fiction course.

A common pattern we found among the topics that each predicted significantly higher attrition in the survival analysis for the Fantasy course was that they expressed confusion with course procedures or a lack of engagement with the course material. In many cases, these students appeared to be excited about the general topic of Fantasy and Science Fiction, but not necessarily excited about this particular course's content. Thus, the specific focus of this course may not have been a good enough fit to keep them engaged. We see students engaged in positive interactions with one another, but not in a way that encouraged them to make a personal connection with the course.

Topic5 [more attrition]. The top ranking words from the model included Philippines, looked, thank, reads, building, seem, intimidating, lot, shortfall, and weirdness. When we examined the texts in the top ranking student-weeks for this topic, the texts did not include many of these or even words found in the list of top 50 ranking words. What this means is that this topic assignment was influenced more by the network connections than by similarities at the word level. When we compared the posts in the top ranking student-weeks, there was indeed a lot of commonality at a more abstract level that might not be visible strictly based on word co-occurrences or word overlap between student-weeks. Many of the posts were introductions and discussions about confusions about course procedures, such as "I've got the same problem here. I think I'll do the assignment anyway; based on what I've read until tomorrow". At first the word *Philippines* seemed puzzling as a top ranking word, however, it was mentioned in several introductions. The word *thank* came up several times when students received a helpful response to their confusion, as in "Thanks; I've sent a request to join". An overwhelming number of these messages about confusion were from the initial week of student participation. Overall, this appears to be a topic that signifies getting oriented to the course and figuring out course procedures. The association with higher attrition is not surprising in that it would be reasonable to expect students to be vulnerable to dropout before they feel settled in a course.

Topic8 [more attrition]. Top ranking words in this topic included https, imaging, regarded, connections, building, course book, hard code, unnoticeable, arises, and staying. The most common connection between top ranking words and the texts in the top ranking student-weeks was discussion about the course books, but also other books the students were interested in, and even a comment indicating more interest in these other books than the ones that were assigned: "I should really start the course books lol". Students talked about their interpretation of symbolism in books and connections in usage of symbolism across books, but again, not necessarily the assigned books. There was some discussion of books versus movies. Overall, the discussion appeared to be lively and engaging, but not necessarily engaged with the assigned content. There was a lot of story telling about the students' own lives and experiences with books from their own countries.

Topic11 [more attrition]. Top ranking words in this topic included childbearing, hitch, range, looks, intimidating, beginning, thanks, behalf, somebody, and feelings. Similar to the other topics we have discussed, in the case of many of the top ranking words, we don't see those exact words showing up in the top ranking student-weeks, but we see words related to them conceptually. For example, the word "feelings" did not show up, but lots of emotional language describing student feelings about books, places, experiences was included. The content in many of the top ranking student-weeks appeared to focus on recommendations passed back and forth between students, sometimes recommending books they had written themselves. Examples include "You might be interested in this.ttp://irishgothichorrorjournal.homestead.com/maria.html" or "Thanks for telling us about it. I can't wait to read it." Similar to topic8, the recommendations were not necessarily for readings that were formally part of the course. Thus, we see students engaged in active exchange with one another, but not necessarily with the curriculum of the course.

Topic13 [more attrition]. Top ranking words include oneself, excitedly, experienced, releasing, somewhere, penalized, commentaries, somehow, thank, and released. Top ranking student-weeks included posts with a lot of troubles talk about the course such as "Well; I'm actually not happy with the essay I submitted. I find it soooooooo very hard to express my thoughts in English", "All is in the eye of the peer reviewing" or "As I am writing the first 'essay'; I have a feeling that I am not writing the essay but a note. I wonder what makes an essay and a note." Students also expressed some explicit disappointment with the readings, as in "i was expecting a real bang up ending. But it just sort of...ends. Oh well." There was also some indication that students came to the course with different expectations than what may have been warranted, as in

> I came to the Discussion Forum looking for answers and the first one I read (yours) dissipates all my doubts. It is true; the name of the course indicates the POV from which we are suppose to be looking at the stories: a neverending interpretation of our modern world and how we explain our existence and that of others in it.

These texts had little overlap with the top ranking word list, but as with earlier topics, we see some conceptual links, such as "oneself" and "our existence". Some student-weeks further down in the rankings that did overlap with the top ranking words were from new students just starting the course, as in "I am so excited to get back to learning."

Accountable Talk course.

Although it was true that the connection between top ranking words and the content of the posts in the topics we examined for the Fantasy course were indirect, they were even more remote in the Accountable Talk course. In fact, we will see that the two identified topics were thematically coherent, but not in terms of word overlap. In both cases we see evidence of strong motivation for students to grapple with the course material and apply it in their own lives, which might explain why these topics were both associated with lower attrition.

Topic8 [less attrition]. Top ranking words include coast, joins, preach, thanks, hello, changed, unsurprised, giver, other, and centered. The top ranking student-weeks had very little overlap with the top ranking words. But the texts within that set were very thematically related with each other nevertheless. The bulk of top ranking student-weeks were focused on discussion about a video in the course called "The Singing Man". Students talked about how inspired they were by the video and how they hoped to be able to achieve these effects in their own teaching, as in "I can't wait to see what explicit training the students received. They were clearly trained to respond to each other and to back up their ideas with the text." There was some troubles talk where participants talked about why they thought this might be hard or where they have struggled in the past in their own teaching. Some non-teacher participants did the equivalent for their own "world", such as parents who talked about their issues with communicating with their children.

Topic12 [less attrition]. Top ranking words included well, partaking, excitedly, fanatic, useable, implemented, naysayer, somebody, applying, and modeled. Many of the top ranking student-weeks for this topic were about questions that students had or things they were wondering about, such as "I was very curious to know how this course could help me in my job as an educator and what type of relationship there is between motivational interviewing and accountable talks", "Hey G; How nice to see you here with my favorite topic: Quote of the day. So what is your most favorite quote. I am keen to know. Thanks!", "For the life of me I cannot find where this pointer is available. I would greatly appreciate your time and consideration in helping me discover this content." These students expressed eagerness to learn or find specific things in this course and to hear the perspectives of others in the course.

Python course.

What is interesting about the Python course is that we have topics within the same course, some of which predict higher attrition and others that predict lower attrition, so we can compare them to see what is different in their nature. Similar to the Accountable Talk course, the connection between the top ranking words in each topic and the topic themes as identified from top ranking student-weeks bore little connection to one another, although we see some inklings of connection at an abstract level. Similar to the Fantasy course, topics that signified higher than average attrition were more related to getting set up for the course, and possibly indicating confusion with course procedures. Like in the Accountable Talk course, topics that signaled lower than average attrition were ones where students were deeply engaged with the content of the course, working together towards solutions. Similar to the findings in the Fantasy course, the interactions between students in the discussions associated with higher attrition were not particularly dysfunctional as discussions, they simply lacked a mentoring component that might have helped the struggling students to get past their initial hurdles and make a personal connection with the substantive course material.

Topic9 [more attrition]. Top ranking words included keyword, trying, python, formulate, toolbox, workings, coursera, vids, seed, and tries. The top ranking student-weeks contained lots of requests to be added to study groups. But in virtually all of these cases, that was the last message posted by the student that week. Similarly, a large number of these student-weeks included an introduction and no other text. What appears to unify these student-weeks is that these are students who came in to the course, made an appearance, but were not very quick to engage in discussions about the material. Some exceptions within the top ranking student-weeks were requests for help with course procedures. This topic appears to be similar in function to Topic5 from the Fantasy course, which was also associated with higher than average attrition.

Topic13 [less attrition]. Top ranking words include name error, uses, mayor, telly, setattr, hereby, gets, could be, every time, and adviseable. In contrast to Topic9, this topic contained many top ranking student-weeks with substantial discussion about course content. We see students discussing their struggles with the assignment, but not just complaining about confusion. Rather, we see students reasoning out solutions together. For example, “So 'parameter' is just another word for 'variable;' and an 'argument' is a specific value given to the variable. Okay; this makes a lot more sense now” or “For update_score(): Why append? are you adding a new element to a list? You should just update the score value.”

Topic17 [more attrition]. Top ranking words include was beginner, amalgamate, thinking, defaultdef, less, Canada, locating, fundamentalist, only accountable, and English. Like Topic 9, this topic contains many top ranking student-weeks with requests to join study groups as the only text for the week. The substantive technical discussion was mainly related to getting set up for the course rather than about Python programming per se, for example “Hi;I am using ubuntu 12.04. I have installed python 3.2.3 Now my ubuntu12.04 has two version of python. How can I set default version of 3.2.3Please reply” or “For Windows 8 which version should I download ?Downloaded Python 3.3.2 Windows x86 MSI Installer?and I got the .exe file with the prompter ... but no IDLE application”.

Topic18 [less attrition]. Top ranking words include one contribution, accidental, workable, instance, toolbox, wowed, meant, giveaway, patient, and will accept. Like topic13, we see a great deal of talk related to problem solving, for example “i typed s1.find(s2;s1.find(s2)+1;len(s1)) and i can't get why it tells me it's wrong? do not use am or pm.... 3am=03:00 ; 3pm=15:00”, or “I don't see why last choice doesn't work. It is basically the same as the 3rd choice. got it! the loop continues once it finds v. I mistakenly thought it breaks once it finds v. thanks!”. The focus was on getting code to work. Perhaps “workable” is the most representative of the top ranking words.

Discussion/Conclusion

In this paper, we have developed a novel computational modeling methodology that provides a view into the evolving social structure within a massive open online course (MOOC). In applying this integrated approach that brings together a view of the data from a social network perspective with a complementary view from text contributed by students in their threaded discussions, we illustrated how we are able to identify emergent subcommunity structure that enables us to identify subcommunities that represent behavior that is coordinated both in terms of who is talking to who at what time and how they are using language to represent their ideas.

In this paper, we have illustrated that this identified subcommunity structure is associated with differential rates of attrition. A qualitative posthoc analysis suggests that subcommunities associated with higher attrition demonstrate lower comfort with course procedures and lower expressed motivation and cognitive engagement with the course materials, which in itself is not surprising. However, the real value in such a model is that it offers a bird's eye view of the discussion themes within the course. The nature of the themes identified is qualitatively different from those identified using LDA alone because of the influence of the network on the topic structure. As pointed out in the qualitative analysis, the semantic connection between high ranking words within a topic is far more indirect than what is achieved through LDA, where word co-occurence alone provides the signal used to reduce the dimensionality of the data. The meaning of the topics is more abstract, and possibly richer, since it represents the collection of themes and values that emerge when a specific group of students are talking with each other.

The purpose of exploratory models such as this probabilistic graphical model is to identify emergent themes and structure in the data. It can be used as part of a sensemaking process, but it is not meant to test a hypothesis. In the case of the analysis presented in this paper, the findings about the association between low engagement and attrition might suggest that it would be worth the effort to formalize the structure so that a more rigorous analysis of the issue could be conducted. Along these lines, in some of our prior work where we have explicitly and directly modeled motivation and cognitive engagement as it is expressed in text only, we have also found evidence that higher expressed motivation and cognitive engagement are associated with lower attrition (Wen et al., 2014). In that work, the effect was much stronger, but it took an investment of time and effort to do the analysis. An exploratory analysis that suggests which issues would be worth investing time to pursue more rigorously within a data set could be valuable from the stand point of being strategic about the investment of research resources, especially when one considers the broad range of research questions that analysis of interaction data affords. The take home message is that exploratory models such as this could usefully be used for hypothesis formation, followed by more careful, direct modeling approach.

A limitation of selecting a probabilistic graphical modeling approach, as with any unsupervised clustering approach, is that the number of topics must be specified before the model is inferred. In our work, we selected a number based on intuition. It should be noted that one can tune the number of features using measures of model fit to determine which number to use. This approach might be especially useful for researchers who prefer not to make an ad hoc choice.

Our long term vision is to use insights into emerging social structure to suggest design innovations that would enable the creation of more socially conducive MOOCs of the future. The lesson we learn from the qualitative analysis presented in this paper is that students are vulnerable to dropout when they have not yet found a personal connection between their interests and goals and the specific content provided by the course. Mentors present within the discussions to coach students to find such personal connections might serve to keep students motivated until they have made it past initial confusions and have settled more comfortably into the course. On average, it is the more motivated students who participate in the discussions at all. However, the analysis presented here reveals that even among those students, we can identify ones that are vulnerable. Real time analysis of the texts could enable triggering interventions, such as alerting a human mentor of an opportunity to step in and provide support to a student who is motivated, but nevertheless does not possess quite enough of what it takes to make it in the course without support. Real time analysis of discussions for triggering supportive interventions that lead to increased learning are more common in the field of computer supported collaborative learning (Kumar & Rosé, 2011; Adamson et al., 2014), and such approaches could potentially be adapted for use in a MOOC context.

The current modeling approach has been applied successfully to Coursera MOOCs in this paper. However, cMOOCs provide a richer and more intricate social structure where students interact with one another not only in threaded discussions, but in a variety of different social settings including microblogs, synchronous chats, and email. Just as the current modeling approach integrates two complementary representations, namely network and text, in future work we will extend the approach to integrate across multiple networks in addition to the text so that each of these social interaction environments can be taken into account. The challenge is that a model of that complexity requires much more data in order to properly estimate all of the parameters. Thus it will likely require jointly estimating a model over multiple courses simultaneously using a hierarchical modeling approach that properly treats within course dependencies within the heterogeneous dataset.

Acknowledgements

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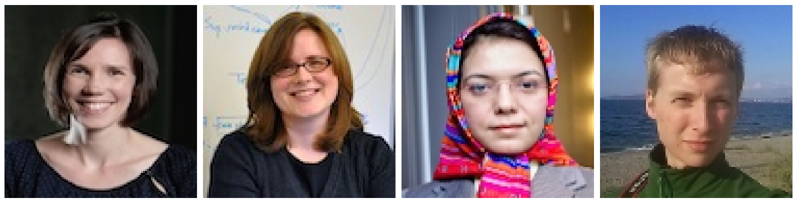
A Comparison of Learner Intent and Behaviour in Live and Archived MOOCs



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Abstract

The advent of massive open online courses (MOOCs) has created opportunities for learning that are clearly in high demand, but the direction in which MOOCs should evolve to best meet the interests and needs of learners is less apparent. Motivated by our interest in whether there are potential and purpose for archived MOOCs to be used as learning resources beyond and between instructor-led live-sessions, we examined the use of a statistics MOOC and a computer science MOOC, both of which were made available as archived-courses after a live-session and for which enrolment continued to grow while archived. Using data collected from surveys of learner demographics and intent, the course database of major learner activity, and the detailed clickstream of all learner actions, we compared the demographics, intent, and behaviour of live- and archived-learners. We found that archived-learners were interested in the live-MOOC and that their patterns of use of course materials, such as the number and sequence of videos they watched, the number of assessments they completed, their demonstration of self-regulatory behaviour, and their rate of participation in the discussion forums, were similar to the live-learners. In addition, we found evidence of learners drawing on an archived-MOOC for use as reference material. Anticipated areas of impact of this work include implications for the future development of MOOCs as resources for self-study and professional development, and in support of learner success in other courses.

Keywords: MOOCs; massive open online courses; archived MOOCs; online education; self-directed learning; self-regulation; remediation

Introduction

Massive open online courses (MOOCs) can provide flexible enrolment options for learners beyond their registered cohort as these courses are often left accessible as self-study after the end of a given session. In this archived-mode, learners continue to be able to access the course materials, although deadlines and the opportunity to earn a credential have passed. In Coursera, for example, about 78% of courses that have finished at least one session on the platform have a session in archived mode (C. Gao, personal communication, November 26, 2013). In this study, we compare the use of two MOOCs as in-session, instructor-led ("live") courses with their use as post-session, self-directed ("archived") learning resources.

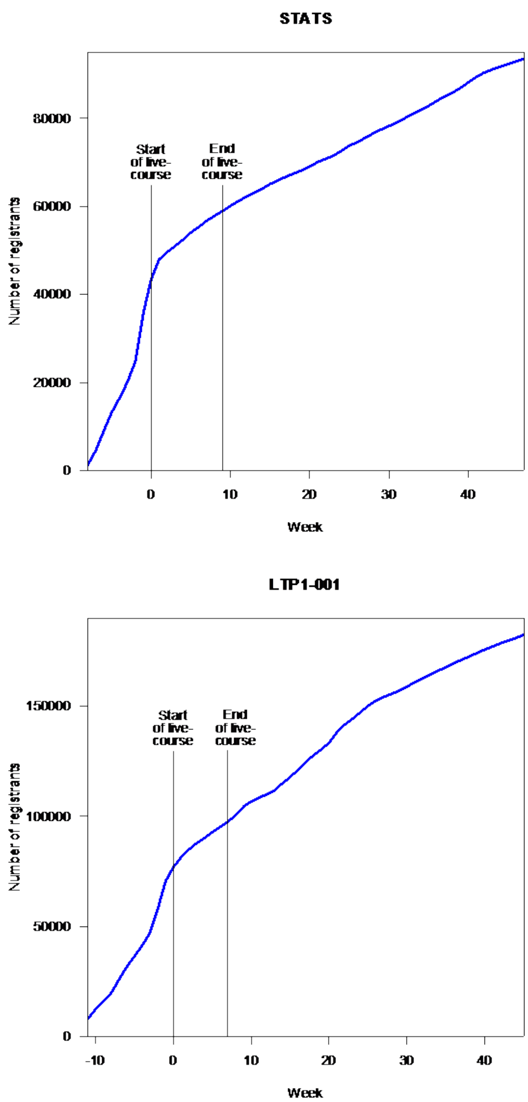


Figure 1. Registration in STATS and LTP1 courses.

The two MOOCs studied here are “Statistics: Making Sense of Data” (STATS) and “Learn to Program: The Fundamentals” (LTP1), offered on Coursera with live sessions in April-May 2013 and September-November 2012, respectively, and available afterwards as archived-MOOCs. When each of these MOOCs ended, many learners persisted and new registrants continued to join the archived courses. Figure 1 shows the number of learners who registered before, during, and after the live sessions of the two courses. We also look at a follow-up course to LTP1, “Learn to Program: Crafting Quality Code” (LTP2), to understand how students transition among related live- and archived-MOOCs.

Purpose of the Study

The purpose of this study is to compare the characteristics of learners and their interactions with two MOOCs during live-sessions and afterwards when the MOOCs are archived. Live- and archived-MOOCs are distinguished by the presence or absence of instructional support, cohort presence, deadlines, and the potential for formal acknowledgement of completion. To this end, we investigated live- and archived-learners' demographics, intent, and the relationship between intended and actual behaviour, including the amount and nature of interaction with the course materials. Our goal in this observational study was to examine learner characteristics and behaviour given the MOOC formats that were available to the learners, allowing us to better understand both who chooses to use the course materials in each format and how they engage with the materials.

Research on MOOC learners has recognized the effect of learner intent on the amount and pattern of MOOC component use (Kizilcec, Piece, & Schneider, 2013). Studying patterns of behaviour of learners who have no chance of earning a Statement of Accomplishment (SoA) or some other formal acknowledgement of completion extends the current state of MOOC research. It also distinguishes this study from the dominant discourse of MOOC research, which is focused on low completion rates and the behaviour and characteristics of learners who do and do not earn an SoA (e.g., Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014).

The purpose of this work is not to critique MOOCs, nor address their known shortcomings such as high attrition rates (Adamopoulos, 2013; Catropa, 2013). We also acknowledge the challenges involved in assessing learning achievement of informal learners (Levenberg & Caspi, 2010), let alone archived-learners. Rather, we aim to understand the similarities and differences between the learning paths of live-learners and archived-learners.

Definition of Terms

Live-MOOC: In-session, instructor-led course with the possibility of obtaining an SoA. The instructional team regularly sends reminders and encouragement through email and announcements to learners. Materials are released at regular intervals and learners are guided through the course at the pace at which the materials are released. An instructional team and cohort provide learning support through the discussion forums. Coursework has deadlines and some coursework includes peer assessment.

Archived-MOOC: Post live-session, self-directed course with minimal or no instructional support or cohort presence, no deadlines, no peer-assessment, and no opportunity to earn an SoA. All materials are available on registration, giving learners more flexibility relative to live-MOOCs in the pace and order in which they access the course materials.

Live-learners: Learners who register in a live-MOOC in time to earn an SoA.

Archived-learners: Learners who are active in an archived-MOOC.

For the purposes of this study, learners are characterized by whether they are accessing the particular live- and archived-MOOCs under consideration, in the form in which these particular MOOCs were available at the time, without consideration to the status of the course when the learners enrolled and how they might be using other MOOCs in which they may be enrolled. In addition, in this study we do not consider other MOOC formats with flexible start dates and pacing such as MOOCs designed for self-study.

Theoretical Framework

Increasing chances for on-demand learning, in the light of intensive interest in life-long learning, is a significant promise and potential of MOOCs (Garrison, 2011). Learners are able to actively choose among available MOOCs to address their professional and learning needs or to pursue personal interests, notwithstanding temporal, geographical, or institutional barriers (Adamopoulos, 2013). Such on-demand learning (Dobrovolny, 2006; Rhode, 2009) is often informal, self-paced, and self-directed online learning. We first examine characteristics of MOOC learning in the light of the aforementioned learning modalities. Then, we examine factors known to impact the quality of learning in this context.

Alongside institution-affiliated online learning, there exist other modalities of online learning that provide to learners greater freedom of choice in duration, content, and modes of assessment (Levenberg & Caspi, 2010). For example, in a self-paced learning mode, students can choose the start date of their course and complete it according to their own time schedule (Anderson, Poellhuber, & McKerlich, 2010; Horton, 2006). Self-paced courses, however, are usually bound by a deadline to finish all course activities and involve some level of real-time or asynchronous instructional support (Gerlich, Mills, & Sollosy, 2009). Learner's choice also applies to the amount of course material and activities that a learner covers.

Similar to other informal and self-paced learning, motivation to pursue learning through MOOCs ranges from career advancement to personal interest (Iiyoshi & Kumar, 2008; Sheu, Lee, Bonk, & Kou, 2013). Live-MOOCs provide an opportunity for informal online learning that can be instructor-led and to some degree self-paced, as learners may often have to stick to deadlines if they strive to earn an SoA and cannot explore course content that is not released yet. Live-learners can also engage in peer interaction, with a defined cohort of students working through the material at the same pace. Archived-MOOCs, on the other hand, fall into the extreme end of the self-paced learning continuum (Lowenthal, Wilson, & Parrish, 2009), as archived-learners have no deadlines to meet and little chance of interacting with course instructors. While interaction with peers is still possible, there is not the same large cohort studying the same material at the same time. Learners can select the material to cover and take as long as they need.

Self-regulation.

Informal learning, such as learning in MOOCs, demands a high level of self-directedness from the learner as they are in charge of their own progress. Self-regulation (Pintrich, 2000; Zimmerman, 2008) explains how learners manage their learning by actively setting goals, planning to achieve their goals, identifying and using resources, monitoring their progress, and using self-corrective measures. We use self-regulation to explain qualities that learners need to develop in order to engage with and persist in informal, non-credit, yet structured, learning environments of MOOCs. Dobrovolny (2006) studied self-paced corporate learners' use of self-regulatory processes using verbal and visual think-aloud strategies. The participants would refer to course material to resolve misunderstandings and confusions, demonstrating self-assessment and reflective strategies. In MOOCs, following each of thousands of learners' self-regulatory processes is not feasible, and it is impossible to provide scaffolding to meet each learner's unique needs. However, clickstream data might provide evidence of learners' self-corrective behaviours, such as accessing relevant resources or posting in discussion forums between repeated attempts at formative assessments.

Learning goals.

Time and effort invested in self-paced courses can be affected by learners' goals and desired achievement levels (del Valle & Duffy, 2009; Ely, Sitzmann, & Falkiewicz, 2009). Within informal learning environments, learners' goals are typically to satisfy their personal interest or further develop their competencies (Sheu, Lee, Bonk, & Kouu, 2013). Time and effort invested in a MOOC may vary from completing all assignments and following the cohort, to selecting relevant topics and studying them at the learner's desired pace (Kizilcec, Piece, & Schneider, 2013). Existing research in self-paced and MOOC learning has mostly focused on learners who complete all course requirements (DeBoer, Stump, Seaton, & Breslow, 2013), excluding the majority of MOOC learners.

Peer collaboration and interaction.

While social presence and its necessity for knowledge co-construction is favoured in online learning community frameworks, such as the community of inquiry (Garrison, Anderson, & Archer, 2000), such interaction among learners in self-paced contexts may be of less importance to their learning outcome. In an exploratory study guided by Anderson's (2003) interaction equivalency theorem, Rhode (2009) interviewed ten learners who completed an online self-paced professional development course. Results showed that participants perceived learner-learner interactions to be challenging and less important than other forms of interactions. Similar findings were reported from a voluntary hybrid professional development course for new faculty, in which learners rarely posted to course discussion forums or replied to their peers' postings (Schwier, Morrison, Daniel, & Koroluk, 2009). More than 70% of self-paced distance learners in the Anderson, Poellhuber, and McKerlich (2010) study preferred working independently to working in groups. Conversely, learners who used fewer resources and invested less time than their peers in a self-paced online professional development course preferred cohort-based learning (del Valle & Duffy, 2009). Although learners value peer-assessment components of MOOCs (Adamopoulos, 2013), high levels of sustained peer interaction may not be viable due to the sheer number of registrants and varied start times. However, based on the existing body of research, motivated learners would persist in the learning environment even with minimal peer interaction. The results of our investigation of the learning strategies of learners in archived-MOOCs, who have little chance for peer interaction, may inform future understanding of learner-content and learner-instructor interaction.

Course content.

Learners' depth of learning is necessarily affected by their persistence with the course. Using text- and opinion-mining methods, Adamopoulos (2013) analyzed 1,163 reviews submitted by 842 learners who had taken at least one MOOC in various disciplines to investigate factors associated with learner retention. While learners' satisfaction with the course material was positively associated with their completion of the course, courses with higher workload and longer duration had greater risk for learner attrition. The importance of the quality of course material on perceived learning, specifically over peer interaction, has also been observed (Rhode, 2009; Schwier, Morrison, Daniel, & Koroluk, 2009). And in a journalism MOOC, 50% and 40% of learners rated course readings and videos, respectively, as being the most helpful learning resources, with only 6% of learners identifying discussion forums as a useful learning resource (Liu, Kang, Cao, Lim, Ko, & Weiss, 2013).

Role of instructor.

In addition to content, the presence of instructional support may influence self-paced, self-directed learners' experiences, but instructional support may be deemed less essential than high quality content (Rhode, 2009; Schwier, Morrison, Daniel, &

Koroluk, 2009). Contradictory evidence was also reported in MOOC settings where instructors were found to be the most important factor in learner retention (Adamopoulos, 2013), but this study does not provide detail on the aspects of the instructors' role that foster retention. The amount of reliance on and interest in instructor interaction may also depend on learners' goals and motivation (del Valle & Duffy, 2009). Considering the large enrollments in MOOCs, high volumes of instructor interaction and feedback may not be feasible or as essential as in formal online courses (Hosler & Arend, 2012; Skramstad, Schlosser, & Orellana, 2012; Sheridan & Kelly, 2010). Archived-MOOCs offering high quality content can be of value to self-paced and self-directed learners, since these learners are less reliant on instructors.

Method

Context of the Study

The learners studied in this research were enrolled in courses that teach practical, skills-based subjects, and for both courses the prerequisite was only high school level mathematics. Moreover, the concepts and skills covered are useful for a variety of professions and fields of study.

We briefly describe the two courses, offered on the Coursera platform, that were used as cases for this study.

- "Statistics: Making Sense of Data" (STATS): This 8-week course provides an intuitive introduction to statistical reasoning. STATS was offered in April-May 2013 in live-mode and was available in archived-mode afterwards. Assessments were seven quizzes and two peer-assessed assignments. Approximately 62,500 learners enrolled by the end of the live-session.

- "Learn to Program: The Fundamentals" (LPT1): LTP1 introduces learners to the fundamental building blocks of programming using the Python language. Two live-sessions of this 7-week course were offered, the first in September-November 2012 and the second in August-October 2013. The course was available in archived-mode between the two live-sessions. Assessments were seven quizzes, three assignments, and a final exam. Approximately 80,000 learners enrolled by the end of the first live-session.

  A sequel to LTP1, "Learn to Program: Crafting Quality Code" (LTP2), was offered in March-April 2013. Approximately 54,000 enrolled in the course by the end of its 5-week live-session.

We study learners in the live- and archived-sessions of STATS. Because of the timing of the conception of this work, we study learners in two sessions of LTP1: archived-learners in the first-session and live-learners in the second-session. We also investigate the activity of LTP2 live-learners who accessed the archive of LTP1, to further understand how learners make use of archived-MOOCs.

Data Sources

Data corpus was collected through the Coursera platform and included the following.

Live-survey: A pre-course survey of live-learners included close-ended questions on demographics, reasons for enrolment, intended time investment, amount of videos and assessments they intended to complete, previous knowledge, and MOOC experience.

Archived-survey: Archived-learners were asked to complete a survey similar to the live-survey with additional questions including why they took the course in its archived-mode and whether they would retake the course in live-mode.

Coursera database: The database contains records of videos accessed, assessments submitted, and posts to the discussion forums.

Clickstream: The clickstream includes a log of all user activity.

All data were anonymized at the institutional level before distribution to the researchers.

Analysis

We used descriptive statistics to better understand the characteristics of live- and archived-learners using the survey data. Data from the clickstream were used to identify learners' patterns of use of the course components. The database of each course provided additional evidence to corroborate and complement this analysis. Anonymized user identifiers provided a map across all data sources, allowing us to connect user behaviour characterized in the clickstream and database with measures of intent captured in the surveys.

Results

We report on learner demographics, intent, and behaviour. Unless otherwise stated, the data presented include only those live- and archived-learners who completed the live- and archived-surveys, respectively. For STATS, 17,541 learners completed the live-survey and 1,923 completed the archived-survey; for LTP1, 28,585 learners completed the live-survey and 2,137 completed the archived-survey. We acknowledge that this population may be different from the population of all learners. However, it is known that many MOOC registrants do not actively participate (e.g., Balakrishnan & Coetzee, 2013) and by restricting ourselves to survey respondents, we are considering a population that is more engaged. Also, we are able to use demographics and learner intent to contextualize behaviour.

Learner Demographics

First, we highlight similarities and differences between demographics of live- and archived-learners, namely age, language proficiency, highest level of education, and reasons for enrolling in the STATS and LTP1 MOOCs. Such descriptive findings further contextualize the results of our clickstream data analysis, as we explain in the following sections.

In both STATS and LTP1, live-learners were younger than archived-learners. In STATS, 85.7% of live-learners and 78.9% of archived-learners were 45 years old or younger; in LTP1, 89.8% of live-learners and 80.0% of archived-learners were 45 years old or younger.

A greater proportion of live-learners identified English as their first language. For STATS, 36.2% of live-learners and 27.0% of archived-learners identified English as their first language. These percentages were 42.8% and 31.8% for LTP1.

Archived-learners in both courses had higher education levels than live-learners with many educated at an undergraduate or postgraduate level. For STATS, 87.9% of live-learners and 92.5% of archived-learners indicated they had completed at least an undergraduate degree, whereas for LTP1, 65.4% of live-learners and 74.0% of archived-learners had at least an undergraduate degree.

Since the experience of archived-learners is of central focus to this research, we examined the reasons why learners chose to enroll in the archived-courses. Figure 2 shows the percentage of survey respondents who selected each possible response as a reason for enrolling in the archived-MOOC. Learners could choose as many responses as applied to them. The top responses for learners in both MOOCs were that they enrolled in the live offering but were not able to complete the course (43.4% for STATS and 41.1% for LTP1), and that they arrived too late for the live offering (30.8% for STATS and 40.9% for LTP1). As these responses indicate, archived-learners were interested in the live-course and most (69.5% of LTP1 and 53.9% of STATS archived-learners) indicated that they would retake it live if it were re-offered.

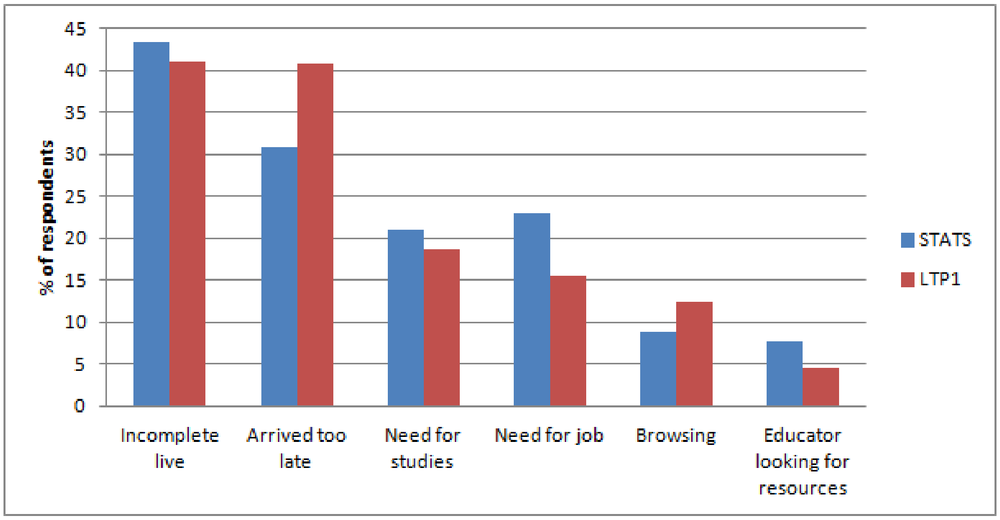


Figure 2. Reasons for enrolling in an archived MOOC.

Learner Intent

Time learners planned to spend.

For STATS, live-learners planned to devote more hours per week to the course than archived-learners (median of 5 hours for the live-learners and 2 hours for the archived-learners). Live- and archived-learners in LTP1 intended to devote a similar number of hours per week to the course (median of 5 hours for both the live- and archived-learners).

Work learners planned to complete.

Learners were asked how much work they planned to do for the course. We have classified their response choices into the following categories.

All required: The learner indicated that he or she planned to complete all requirements, including watching all videos, and completing all assessments.

Most: The learner indicated that he or she planned to watch most videos and complete some assessments.

Not sure: The learner indicated that he or she was unsure.

Some: The learner indicated that he or she planned to watch some videos, perhaps on targeted topics, but was unlikely to complete assessments.

Table 1 shows the percentage of learners in each category. Perhaps motivated by the opportunity to earn an SoA, more live-learners intended to complete all requirements. For STATS, the relatively low percentage of archived-learners who planned to complete all requirements may be a reflection of the fact that the peer-assessments could not be completed in archived-mode.

Table 1

Summary of Work Learners Planned to Complete

	STATS		LTP1	
	Live	Archived	Live	Archived
All required	74.8%	39.3%	81.8%	65.3%
Most	11.4%	25.9%	7.0%	12.7%
Not sure	11.2%	9.0%	10.1%	12.3%
Some	2.5%	25.8%	1.1%	9.6%

Learner Behaviour

Overview.

Table 2 provides summary statistics about the behaviour of learners in the live- and archived-MOOCs, as characterized by how many videos they accessed, assessments they attempted, and the time between first and last video access.

The average number of required videos accessed is similar for live- and archived-learners in STATS, but LTP1 live-learners watched, on average, about two more videos than archived-learners. While live-learners complete slightly more assessments than archived-learners, the difference is small. The optional videos in STATS are tutorials in the R statistical software and programming language. Archived-learners watch, on average, approximately one more of these videos than live-learners.

We defined access time as the number of days between the first and last access of any video. In this analysis we are only considering archived-learners who had been enrolled for at least the length of the live-MOOC. For both STATS and LTP1, over 50% of learners accessed videos for at most 10 days in both the live- and archived-courses. However, for the learners in the top quartile of video access times, more archived-learners than live-learners had long access times. Archived-learners in the 90th percentile accessed videos over a period of 150 days or more, while for live-learners the 90th percentile was approximately 50 days. Thus even the live-learners who had the longest access times tended to not access the MOOCs after their formal conclusion, while some archived-learners access the learning resources over long periods of time. Note that, because the last day of access was necessarily constrained by the date on which the clickstream was extracted, some larger access times are censored, possibly underestimating the 90th percentile for archived-learners.

Table 2

Summary Statistics of Live and Archived Learner Activity

		STATS		LTP1	
		Live	Archived	Live	Archived
Number of required videos accessed (maximum 41)	Mean Median	12.1 7	12.2 5	15.2 10	13.5 7
Number of optional videos accessed (maximum 24)	Mean Median	2.7 1	3.5 1		
Number of required quizzes attempted (maximum 7)	Mean Median	2.5 1	2.1 0	2.2 1	2.0 1
Number of required assignments attempted (maximum 3)	Mean Median			0.7 0	0.9 0
Length of time between first and last video access (days)	Median 75th percentile 90th percentile	11.1 41.9 55.2	12.0 52.5 149.4	12.4 40.1 49.5	9.6 50.0 171.6

Sequencing of videos watched.

Archived-learners who enroll after the live-MOOC has ended have immediate access to all lecture videos. As a result, they have much greater opportunity than live-learners to explore the course in a non-sequential fashion, perhaps picking and choosing topics that are of interest to them.

To investigate this behaviour, we model a learner's transition from video to video using a first-order Markov Chain. The statistics of interest are captured in a video-by-video matrix; rows are the last video watched, columns are the next video watched, and the entry is the estimated probability that a learner will make this transition. Since we are interested in transitions between videos rather than rewatches of the same video, we exclude self-transitions.

Figures 3, 4, 5, and 6 give visual representations of these transition matrices. Hotter colours indicate larger probabilities, corresponding to more common video-to-video transitions. A hot spot immediately to the right of the diagonal indicates the transition of watching a video in sequential order.

In STATS, it was very common for both live- and archived-learners to follow the intended sequence, as indicated in the strong pattern from upper-left to lower-right, one to the right of the diagonal. Figures 3 and 4 illustrate the transition matrices for learners whose intent was categorised as all required and most. The strong sequential pattern in video transitions exists regardless of intent.

For LTP1 learners who indicated they intended to do all of the required work for the course, both live- and archived-learners also tend to watch the videos in sequence (Figure 5). However, for learners who intended to do less than all of the work, video transitions were more sequential in the live-course than in the archived-course. In Figure 6 we illustrate the matrix for the learners who responded in the category most for intent; a similar pattern was observed for learners who intended to do some or who indicated that they were not sure.

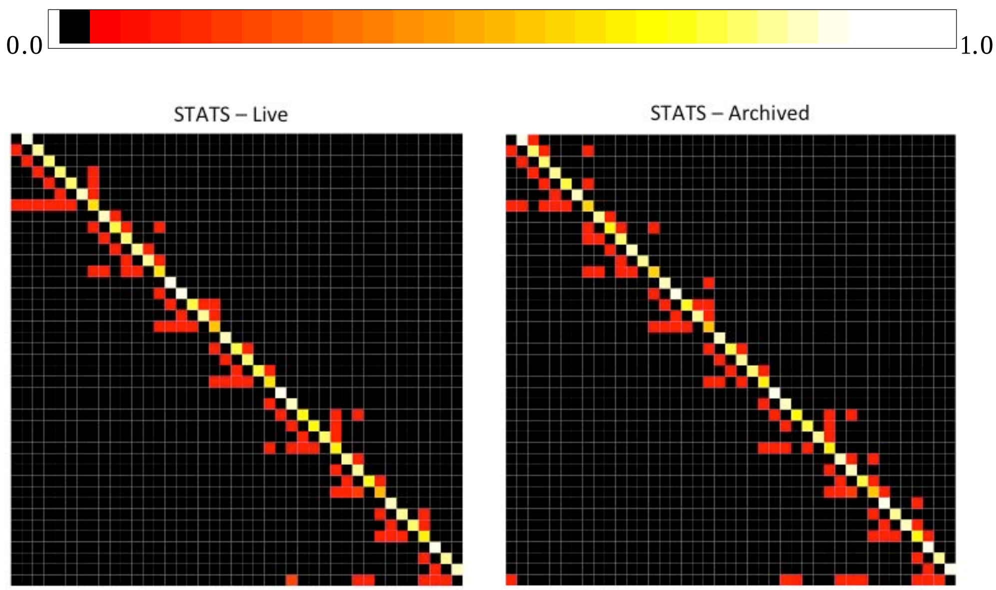


Figure 3. Video transition matrices for STATS, intent category all required.

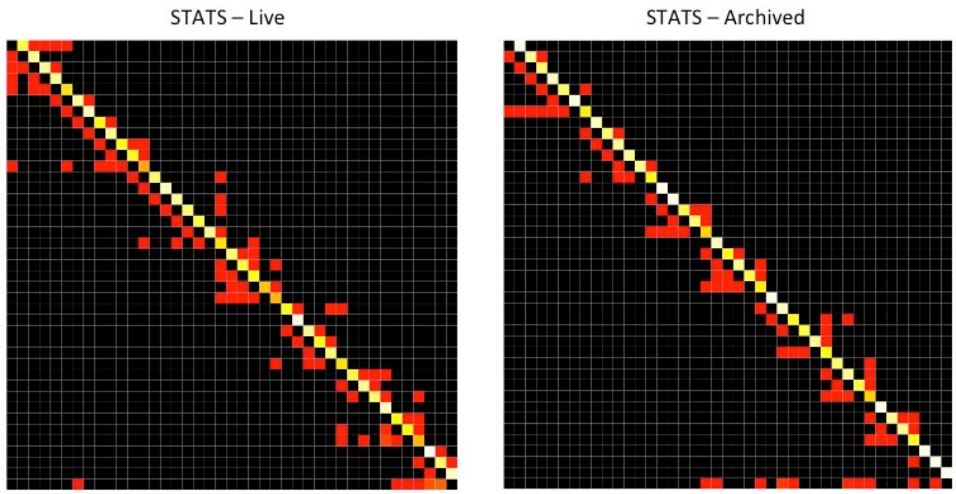


Figure 4. Video transition matrices for STATS, intent category most.

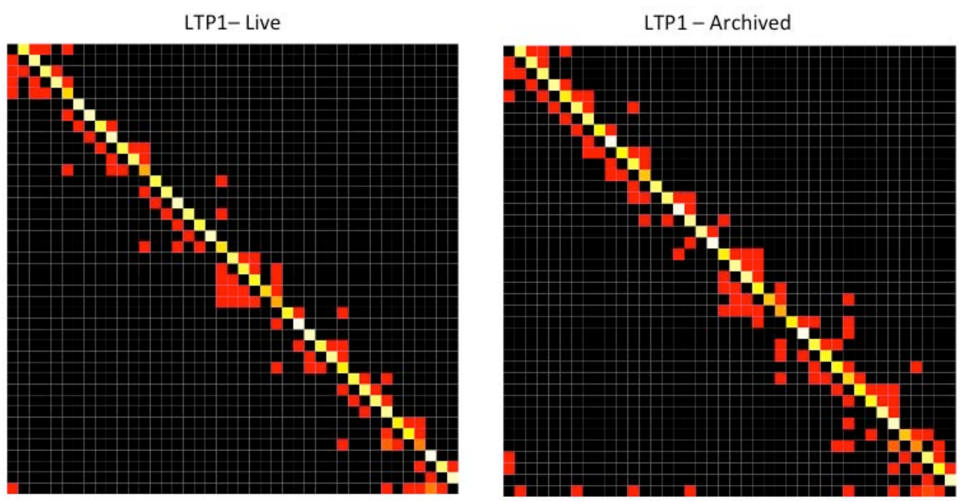


Figure 5. Video transition matrices for LTP1, intent category all required.

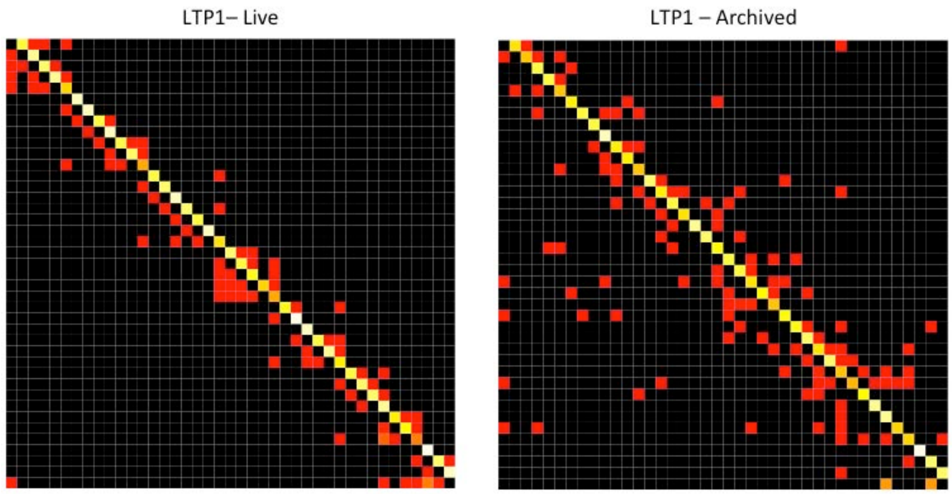


Figure 6. Video transition matrices for LTP1, intent category most.

Quantity of assessments completed.

Archived-learners cannot earn a Statement of Accomplishment, so we cannot use earning an SoA as a metric of course completion. Quiz completion is one possible alternative measure of course completion. For STATS, Figure 7 shows the proportion of learners for each possible number of quizzes completed, broken down by intent. For both live- and archived-learners, learners more commonly completed zero or all seven quizzes. The largest proportion of those who completed all seven quizzes was observed for learners who intended to complete all required in the archived-MOOC (35.7%).

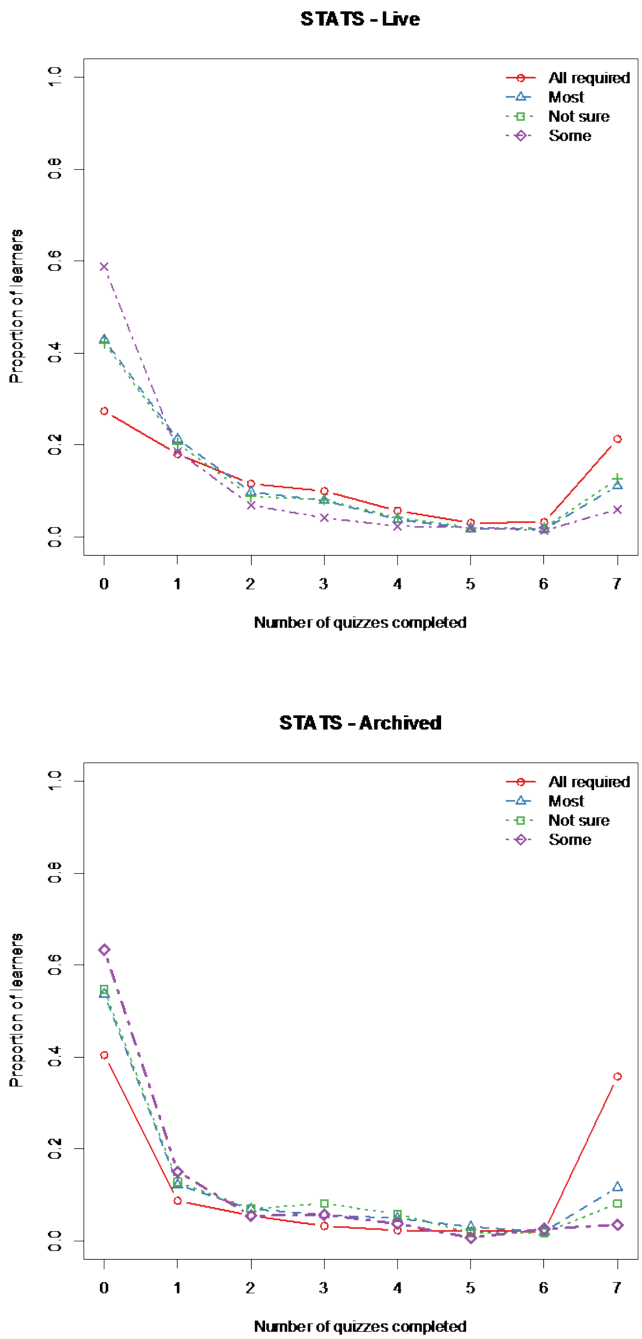


Figure 7. Number of quizzes completed by STATS live- and archived-learners, by intent.

Overall, the pattern was similar for both quizzes and assignments in LTP1, as shown in Figures 8 and 9. However, the proportion of learners who completed all seven quizzes is not as prominent in the live-course, perhaps indicative of the fact that an SoA could be earned without completing all quizzes.

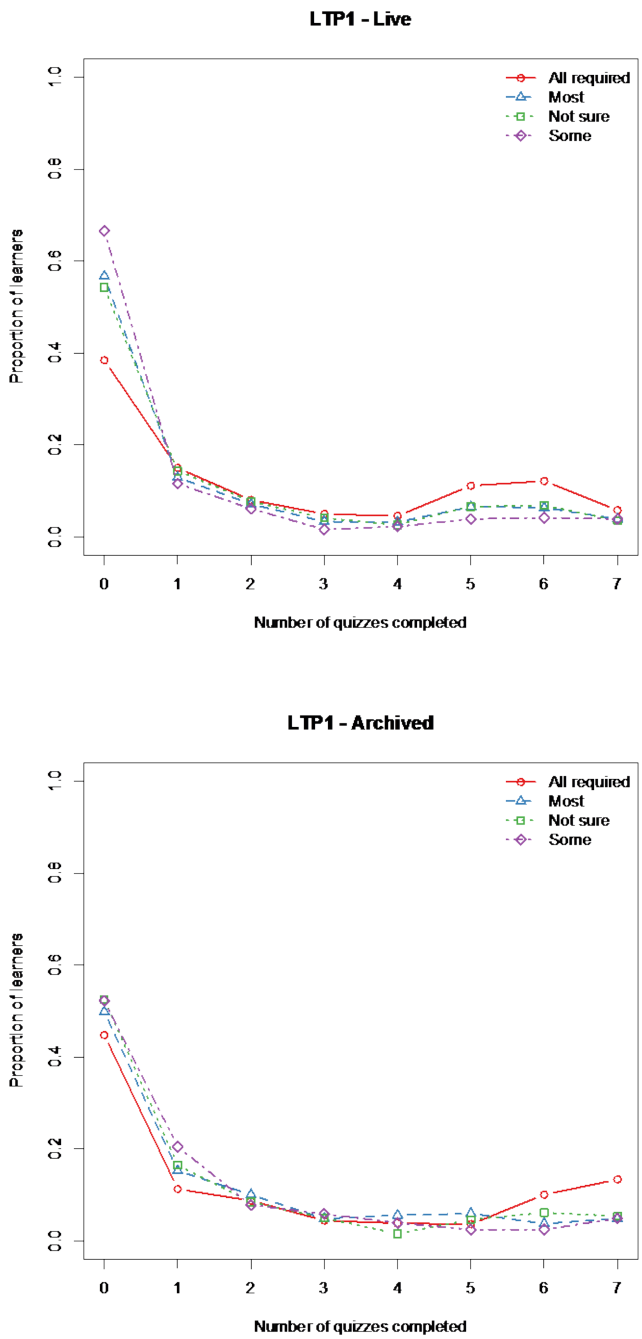
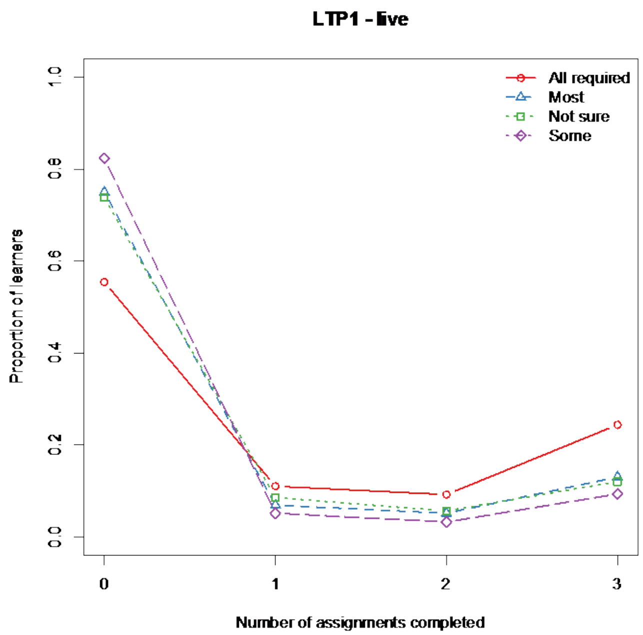


Figure 8. Number of quizzes completed by LTP1 live- and archived-learners, by intent.



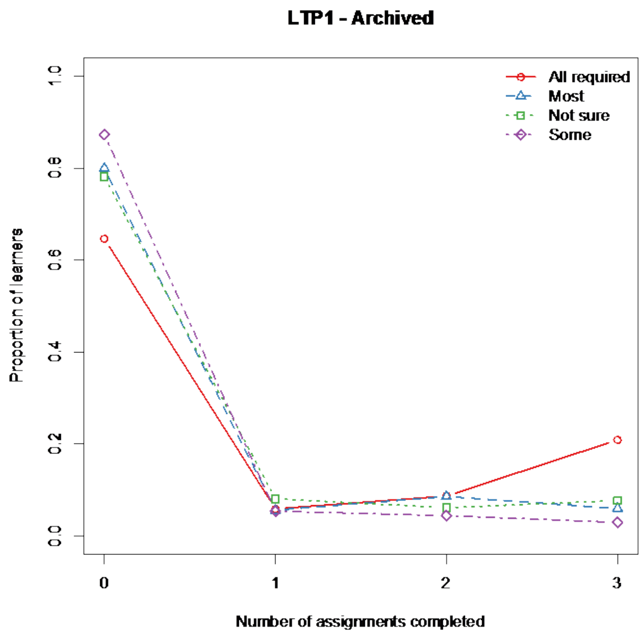


Figure 9. Number of assignments completed by LTP1 live- and archived-learners, by intent.

Discussion forum interactions.

We also investigated discussion forum activity for live- and archived-learners. More of the live-learners (44.6% for STATS; 41.8% for LTP1) view threads than archived-learners (31.3% for STATS; 37.3% for LTP1). Of those who do view threads, the mean number of views for STATS live-learners was 10.9 and archived-learners was 14.5, whereas the mean for both live- and archived-learners in LTP1 was 19.6.

As is typical of MOOCs, the number of learners who post or comment on the discussion forums is low for both live- and archived-learners (DeBoer, Ho, Stump, & Breslow, 2014). In both STATS and LTP1, more live-learners (12.1% for STATS and 14.5% for LTP1) posted than archived-learners (9.3% for STATS and 13.2% for LTP1). It is interesting to note that archived-learners did post to the forums, even though the courses were not active. The mean number of posts by those archived-learners who do post was 5.1 for STATS and 3.9 for LTP1.

Activity patterns: activity between reattempts of an assessment.

In both STATS and LTP1, learners were allowed multiple attempts at the quizzes and the maximum grade achieved counted towards their course assessment. As an investigation of the relative evidence for self-regulatory activity in the live- versus archived-courses, we examined the frequency of use of MOOC materials, in particular lecture videos and forums, between repeated attempts at machine-graded quizzes.

In Figure 10, we see that a greater percentage of archived-learners in both courses accessed lecture videos between quiz reattempts, although this behaviour is less evident for the later quizzes. As can be seen in Figure 11, archived-learners use the forums as a resource for self-regulated learning at least as much as learners in the live-course. Although not shown here, no distinguishing patterns were observed among learners' varying levels of intent.

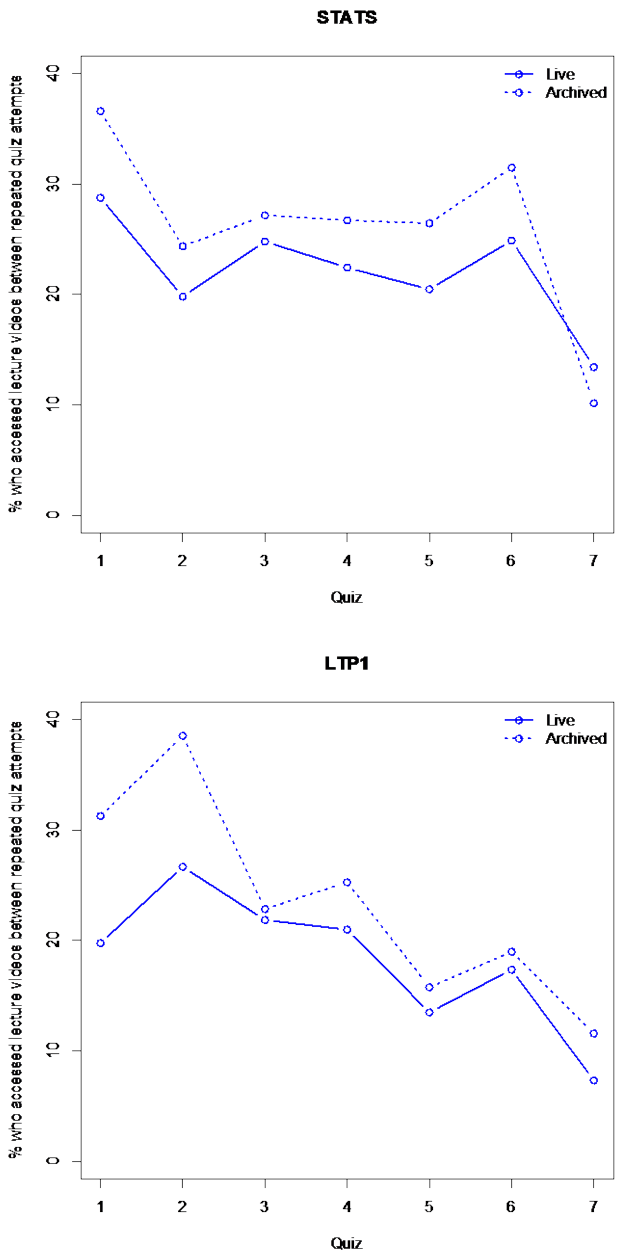


Figure 10. Percentage of learners who reattempted quizzes who accessed lecture videos between reattempts.

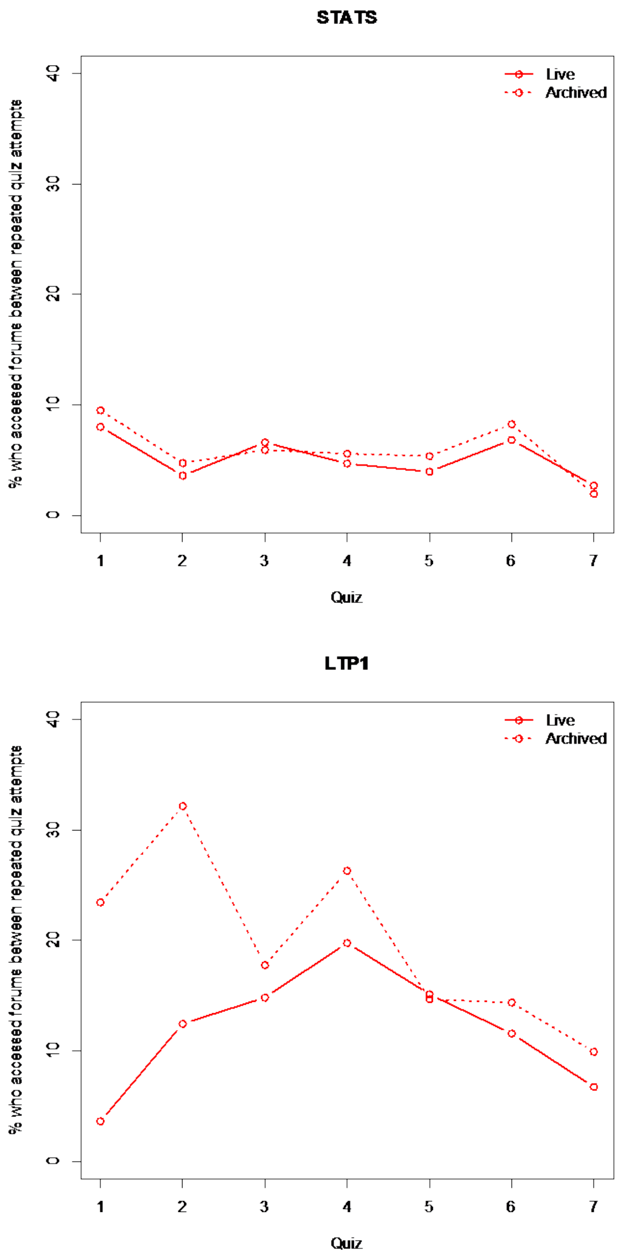


Figure 11. Percentage of learners who reattempted quizzes who accessed discussion forums between reattempts.

Activity patterns: LTP2 learners active in LTP1.

LTP2 was a sequel to LTP1, with the content from LTP1 a presumed prerequisite. During the period when LTP2 was live, LTP1 was available as an archived course, and thus was accessible reference material for learners enrolled in the live offering of LTP2.

Of the 16,875 active live-learners in LTP2, 2,192 (13.0%) were active in the archived LTP1.

Here we report on the activity in the archived-LTP1 of those 2,192 LTP2 live-learners. We are only reporting on activity of these learners while LTP2 was live, so the access time available is less than that for the general LTP1 archived-learner population. It appears that watching videos was the primary reason for using the LTP1 archived course, with less interest among these learners in accessing assignments and discussion forums.

Almost all of these learners visited LTP1 to view videos, with 93.1% accessing at least one LTP1 video, and, on average, 9.4 videos accessed. Only 3.7% accessed all of the LTP1 videos. Relative to the general population of LTP1 archived-learners (see Table 2), the LTP2 live-learners access an average of 4.1 fewer videos.

Fewer LTP2 live-learners who concurrently accessed LTP1 completed LTP1 assessments. 73.7% did not submit any quizzes and 92.5% did not submit any assignments. Only 0.8% completed both all seven quizzes and all three exercises.

The LTP1 forums were not a popular resource for the LTP2 live-learners, with over 75% of them viewing either no threads or a single thread once.

Discussion

MOOCs commonly have defined start and end dates for a cohort but remain open after the end date with learners continuing to enroll. Can these archived courses meet learners' needs? Our goal in this research was to examine learner characteristics and behaviour in live- and archived-MOOCs. We found more similarities than differences, with indications that archived-learners interact with the course in much the same way as live-learners. These similarities are consistent with the top reasons why learners used the archived course materials, which were because they arrived too late in the live-course or they were unable to complete the course during the live-session. Since this is an observational study, we cannot attribute differences between learners and their behaviours to the differences between live- and archived-MOOCs.

Previous research on self-directed learning in MOOCs (Kizilcec, Piece, & Schneider, 2013) and other settings (de Valle, & Duffy, 2009) has stressed the connection of learners' intent to their level of engagement with learning and assessment resources. Here we took a step towards understanding this relationship by including in our analysis learners who would not be acknowledged externally for their learning effort such as by earning an SoA. Although not as many as for the live-courses, significant proportions of the archived-learners indicated that they planned to complete all required work. Even though fewer archived-learners indicated that they intended to complete all required work, the mean numbers of videos accessed and assessments attempted are similar for live- and archived-learners. In both the live- and archived-groups, learners who intended to complete all of the required work tended to complete either none or all of the assessments. This may indicate that learners who find the course meets their needs make that decision very early in the course and, having made that decision, act accordingly.

A common topic in the MOOC literature is retention (Breslow et al., 2009; Chen et al., 2012). The existence of instructional support and a peer cohort created a social structure that we thought might positively impact retention in the live-MOOCs. However, archived-learners achieved similar progress, watching a comparable number of videos and displaying a similar pattern in the particular assessments that were attempted. In the archived-MOOC, the flexible pace may have been a contributing factor to this retention, as also seen by Gooding et al. (2013). Yet there is tension between providing the flexibility of archived-MOOCs and the strong social support structure of live-MOOCs, illustrating the potential for continued improvement of MOOC formats.

An important component of live-MOOCs is the online discussion forum. In the archived-MOOCs, despite the lack of instructional and reduced cohort presence on the forums, there was still extensive discussion forum use. Bruff et al. (2013) found that an on-campus cohort of learners using an archived-MOOC viewed forums posts, but few reported posting to the forums themselves. Instead, they chose to ask questions locally. Our archived-learners, in the absence of a recognizable cohort, both viewed discussion forums posts and posted to the forums.

Although the archived questions and answers were not recently posted, they remained a valuable resource for archived-learners. These forums became another medium for content delivery, rather than an opportunity for social interaction. Existing research (Anderson, Poellhuber, & McKerlich, 2010; Rhode, 2009; Schwier, et al., 2009) has shown that learners value course content over peer and instructor interaction. For our archived-learners, less peer interaction and a minimal chance of instructor interaction did not generally deter them from covering their intended content. Their reasons for and the extent of their desired interaction with instructor and peers, however, remain open questions that are beyond the scope of this study. An investigation into these questions would inform the potential development of a new modality for self-directed, on-demand learning that combines the self-paced structure of an archived-MOOC with the desired instructional support structure.

Live-learners had the opportunity to earn an SoA and all learners had the opportunity to re-take quizzes to demonstrate mastery. In both groups of learners, indications of self-regulatory behaviour were observed in remedial action taken between repeated attempts at quizzes. Archived-learners used the lecture videos and the discussion forums as resources for self-regulated learning at least as much as learners in the live-course, even though there was no external reward for improved results.

With all course materials immediately available on registration, archived-learners have the opportunity to view the videos in the order of their choosing, rather than being limited by the release of materials at regular intervals. We had hypothesized that archived-learners may be more likely to explore the course in a non-sequential fashion, picking and choosing topics that were of most interest to them. However, for archived-learners who intended to complete all required work, the sequence of videos accessed closely matched the sequence that the instructor intended. Thus learners are treating the archived-MOOC as a traditional course, rather than as a learning resource they might access as needed. However, the use of archived-LTP1 by LTP2 live-learners illustrates that there is potential for archived-MOOCs to be used as reference material as well.

Archived-learners have more flexibility, not only in terms of access to content but in the pace at which they complete the course. Additional exploration of the pace at which archived-learners access videos and complete assessments may have valuable implications for course design.

In this study, we investigated two MOOCs, both of which had live-sessions followed by a period of time during which the MOOCs remained available as archives of the live-sessions. Archived-learners are interacting with the courses in much the same way as live-learners. They succeed at the same rate as live-learners, with minimal guidance and no obvious cohort. There is potential for MOOCs to be beneficial as self-study courses, and for the development of new modalities that combine the most valued aspects of live- and archived-MOOCs to best meet learner needs and interests.

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A Social Network Perspective on Peer Supported Learning in MOOCs for Educators

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Abstract

A recent phenomenon in the MOOC space has been the development of courses tailored to educators serving in K-12 settings. MOOCs, particularly as a form of educator professional development, face a number of challenges. Academics, as well as pundits from traditional and new media, have raised a number of concerns about MOOCs, including the lack of instructional and social supports. It is an assumption of this study that challenges arising form this problem of scale can be addressed by leveraging these massive numbers to develop robust online learning communities. This mixed-methods case study addresses critical gaps in the literature and issues of peer support in MOOCs through an examination of the characteristics, mechanisms, and outcomes of peer networks. Findings from this study demonstrate that even with technology as basic as a discussion forum, MOOCs can be leveraged to foster these networks and facilitate peer-supported learning. Although this study was limited to two unique cases along the wide spectrum of MOOCs, the methods applied provide other researchers with an approach for better understanding the dynamic process of peer supported learning in MOOCs.

Keywords: MOOC; social network analysis; online learning; communities of practice

Introduction

MOOCs, or massively open online courses, have gained extensive media attention for their vast enrollment numbers and the alliance of prestigious universities collectively offering free courses to learners worldwide. Though MOOCs have primarily consisted of undergraduate level courses at these respective colleges, early reports on participant demographics suggests that a typical MOOC 'student' already holds a bachelor's or master's degree and is employed full- or part-time (Balch, 2013; Belanger & Thorton, 2013; Kizilcec & Piech, 2013; University of Edinburgh, 2013). For many, MOOCs are filling the role of continuous education and ongoing professional development, serving to satisfy personal intellectual curiosity or enhance the workplace skills of post-graduates.

A recent development in the MOOC space has been the growing number of courses tailored to educators serving in K-12 settings. In April, 2013, the Friday Institute for Educational Innovation at North Carolina State University, in partnership with the Alliance for Excellent Education, launched MOOC-Ed.org along with its first course aimed at supporting school technology leaders (Kleiman, Wolf, & Frye, 2013). Shortly after, Coursera announced a partnership with leading schools of education and cultural institutions, to open up a series of training and development courses for teachers worldwide (Empson, 2013). Education leaders, such as former governor of West Virginia and President of the Alliance for Excellent Education Bob Wise (2013), see MOOCs as a means for schools and districts facing slashed budgets and increasing demands to provide personalized professional development at a fraction of the cost of traditional models. MOOCs as a new model of online professional development present new opportunities and pose new challenges. MOOCs typically provide little or no instructional support beyond the prepared videos and course materials posted by professors and staff. Due to their scale, even MOOCs with active instructors make it impossible to provide the level of instructional feedback and support that would be expected in smaller face-to-face or conventional online course settings.

This problem of scale, however, presents a unique opportunity for social networking and the development of peer support networks to fill this instructional void. In a report commissioned by the Canadian government to study the implications of MOOCs for the digital economy, McAuley, Steward, Siemens, and Cormier (2010) noted that MOOCs have the potential to "model and build collaborative networks of unprecedented size that transcend time and space" and the "network ties created between people during a MOOC have the potential to continue as sustainable and relevant personal and professional connections beyond the boundaries of the course itself" (p. 35). This case study adopts a social network perspective in order to investigate peer interaction and support in two MOOCs designed for the professional development of K-12 educators (MOOC-Eds).

The Social Network Perspective and MOOCs

It is only in the past couple of decades that network thinking has gained considerable attention in academia, as noted by Borgatti and Foster (2003) in the exponential growth of publications on “social networks.” Research in education has followed a similar trend, which Mcfarland, Diehl, and Rawlings (2011) attribute “not only to a growing awareness of networks brought on by the popularity of social networking sites like Facebook and Twitter, but also as a result of statistical breakthroughs and substantial increases in computing power” (p. 88). While social learning theories such as social cognitive theory and social constructivism have become an accepted part of our knowledge base for understanding the learning process (Bandura & McClelland, 1977; Grusec, 1992; Wu, Tennyson, & Hsia, 2010), educational researchers have noted the limitations of these theories in the digital age (Bell, 2011). In their theory of connectivism, Siemens (2005) has described learning as a process of network formation, with connections being key to networked learning, while Downes (2009) asserts that knowledge consists of the network of connections formed from experience and interactions with a knowing community.

The process of network formation described by Siemens, specifically the development of peer-support networks, is of primary interest to this study. In their review of the literature, Rivera, Soderstrom, and Uzzi (2010) classify these processes into three broad mechanisms: 1) assortative mechanisms, 2) relational mechanisms, and 3) proximity mechanisms. Assortative mechanisms theorize that the creation, persistence, and dissolution of ties between individuals are “outcomes that rely on the compatibility and complementarity of actors’ attributes” (p. 94). One assortative mechanism is *homophily*, or the tendency for individuals in the physical and virtual world to show a preference for interacting with others who share similar characteristics such as gender, age, ethnicity, and education level. Although this social phenomenon and its effects have been studied across a variety of offline educational settings (Burgess, Sanderson, & Umaña-Aponte, 2011; M. H. Jones, Alexander, & David, 2010; Rocca & Mccroskey, 1999), our understanding in online learning settings is limited (Yuan & Gay, 2006). Stepanyan, Borau, and Ullrich (2010) examined homophily and popularity effects among students utilizing Twitter as part of an English language course at a university in Shanghai and found a preference among students to “follow” and communicate with other students with similar academic grades histories. Homophily has also been examined in the context of school reform. Penuel et al. (2010) examined the impact of a school-wide reform effort to improve teacher collaboration around literacy instruction at two elementary schools. The researchers found that in the school that had not succeeded in enacting significant reforms, there continued to be a fractured social network where subgroups were defined by homophily, while in the successful school they found “a cohesive advice network with subgroups aligned to the formal organization of the school into grade-level teams... and a coach who played a central role within the advice network” (p. 63).

Relational mechanisms emphasize the impact that the network's structure has on the formation of ties and encompasses network effects such as reciprocity, transitivity and actor prestige. For example, *reciprocity* (e.g., communications involving back-and-forth exchange) has been described as one of the defining attributes of any network, real or virtual (Aviv, Erlich, Ravid, & Trotter, 2008). However, evidence for reciprocity as a mechanism in online social spaces, that is knowledge exchanges between two parties that are mutual and perceived as fair by both parties, is mixed. Wang and Noe (2010) reported on the relationship between the norm of reciprocity and knowledge sharing in the context of communities of practice and noted that a third party rather than the original recipient often reciprocates an individual's knowledge sharing in communities of practice. Chiu et al. (2006), on the other hand, investigated knowledge sharing in an IT-oriented professional learning community in Taiwan and found that the degree to which participants' felt a norm of reciprocity was positively associated with individuals' frequency of their sharing knowledge, though not the quality of their postings. These mixed results reflect those of other studies of network interaction in online virtual communities (C.-J. Chen & Hung, 2010; Hew & Hara, 2007; C. Wang & Lai, 2006). The evidence suggests a pattern of generalized exchange, which Cropanzano and Mitchell (2005) describe as a process of "group gain":

> [B]enefits are put into a single common "pot" and individuals take what they need from this common pool regardless of their particular contribution. Likewise, they contribute to this cache when they are able. Notice that the exchange is not directly transacted from individual to individual. Rather, all things are held in common. Group gain does not involve dyadic or interpersonal exchanges; rather, all things are held in common. (p. 879)

Research also suggests that actors who are more spatially proximate, that is, live or work near one another, are more likely to form social ties. These mechanisms have been found to shape social networks in both physical and online settings. Barab, MaKinster, and Scheckler (2003) noted that proximity in terms of physical location influenced whether members of work teams collaborated with each other, even when team members were spread out over geographic distances and were working together through online collaborative tools. Huang, Shen, and Contractor (2013) reported similar findings in terms of proximity among members of gaming communities, while Yuan and Gay (2006) found that proximity as well as other shared sociodemographic characteristics influenced network ties even among individuals who have only interacted through computer-mediated communication.

Finally, social network theory posits that the structure of social relations can facilitate or inhibit outcomes for individuals and has been used to explain a wide variety of phenomena in the social sciences (S. Borgatti, Mehra, Brass, & Labianca, 2009). In online learning settings such as higher education, studies have found relationships between network measures and academic outcomes like knowledge construction (Aviv, Erlich, Ravid, & Geva, 2003; Rossi, 2010), academic performance (Cho, Gay, Davidson, & Ingraffea, 2007; Russo & Koesten, 2005), and positive dispositions toward the learning experience (Dawson, 2008; Lowes, Lin, & Wang, 2007). The process of knowledge co-construction in online learning spaces in particular has received considerable attention by network researchers in education (Aviv et al., 2003; Heo, Lim, & Kim, 2010; S. Wang & Noe, 2010; Zheng & Spires, 2012). Wang and Noe (2010) examined the relationship between knowledge construction and learners' positions at the core, core-periphery, and periphery of the network and found that the closer students are to the "core" of a network, the more active they are in the "information-sharing" and "negotiation of meaning" levels of knowledge building.

Although still in its infancy, the MOOC literature to date has explored topics as diverse as self-regulated learning (Littlejohn, 2013), user attributes and behaviors (Aiken, Lin, Schatz, & Caballero, 2013; Belanger & Thorton, 2013; Breslow et al., 2013; Deboer, Stump, Pritchard, Seaton, & Breslow, 2013), completion rates (Clow, 2013), and learning analytics (Fournier, Kop, Sitlia, & others, 2011; Seaton, Bergner, Chuang, Mitros, & Pritchard, 2013; Sinha, 2012). A handful of studies have even addressed learning as a social process (Cabiria, 2008; Levy, 2011; Mak, Williams, & Mackness, 2010; Viswanathan, 2012). In this review, however, only one study proposed research to explore networked learning by "experimenting with social network analysis to see if it yields findings about the nature and longevity of group formation" (Breslow et al., 2013, p. 23).

The above review of the literature highlights the potential for network thinking to expand our understanding of the learning process as a social endeavor. However, there is a need for more research in the field of education, and online learning in particular, that explores mechanisms shaping network processes. In addition, studies that have examined network outcomes such as knowledge construction have drawn their data from college-level online courses where participation is tied to course grades and discussion forums are highly structured by an instructor. This study aims to address these gaps in the MOOC literature through social network analysis (SNA) and qualitative methods that explore the processes and product of peer support networks in two MOOC-Eds.

Methodology

This study employs a mixed-method case-study design. The case study approach is well-suited for studying emerging complex social phenomenon in a natural setting in which the investigator has little or no control (Yin, 2009).

This study is framed by three primary research questions related to peer supported learning:

RQ1. What are the patterns of peer interaction and the structure of peer networks that emerge over the course of a MOOC-Ed?

RQ2. To what extent do participant and network attributes (e.g., homophily, reciprocity, transitivity) account for the structure of these networks?

RQ3. To what extent do these networks result in the co-construction of new knowledge?

Yin (2009) states that an important component of case study research is the development of theoretical propositions used to guide the study. Each proposition, Yin notes, directs attention to something that should be examined within the study. One aim of this study is to find commonalities that describe educator interaction patterns within MOOCs and identify mechanisms that are predictive of social ties. Based on the theoretical framework and the above literature review, three theoretical propositions for network processes are also put forth below.

Early findings in network research have also noted tendencies for a small proportion of individuals in social networks to have a disproportionate number of social ties (Rivera et al., 2010). These types of networks are commonly referred to as scale- free networks and their degree distribution, that is, the number of ties each actor in the network has, follow a power law distribution rather than a normal curve. This skew in the number of ties has been noted by Wenger who asserts that CoPs typically consist of a small core group of active participants who participate quite frequently and assume community leadership; a small active group of members who participate regularly but not as frequently as the core group; and a large portion of members, peripheral participants, who rarely participate (Wenger et al., 2002). Findings from the literature suggest this core-periphery structure is common among large online communities, including online learning communities.

P1. The social network is likely to be characterized by a small core of highly connected individuals, with a large proportion of actors surrounding the periphery of the core.

Researchers have suggested that reciprocity is one of the defining attributes of any network, real or virtual, and that an individual forms a tie with someone who has already related to him or her, or with someone who is a promising resource and will probably reciprocate (Aviv et al., 2008). However, evidence for reciprocity, that is, knowledge exchanges between two actors that are mutual, as a mechanism in non-education related online networks is mixed. Although Hakkinen and Jarvela (2006) found evidence of reciprocity among pre-service teachers in a web-based course, Aviv et al. (2008) hypothesized that in distance learning networks, levels of reciprocity would be no greater than would be expected by chance due to limited face-to-face contact and discussions being limited in scope and time. To their surprise, they found that in all 95 internet-based networks formed in Open University of Israel courses, reciprocity was observed beyond what would be expected by chance in all networks. Thus, the following proposition is put forth:

> P2. Reciprocity will have a positive effect on tie formation in MOOC-Eds.

Finally, assortative mechanisms speculate that the creation, persistence, and dissolution of social ties are all outcomes that rely on the compatibility and complementarity of actors' attributes, while proximity mechanisms suggests that actors who are closer geographically are also more likely to form a tie (Rivera et al., 2010). As detailed earlier, network researchers have provided evidence of homophily and proximity in the formation of network ties, even in academic settings where similarity is not a necessary condition for learning, and where learners have only interacted online. As new ties are more likely to form between individuals who share similar characteristics, homophily and geographical proximity are likely to play an important role, especially in a MOOC environment where participants are unlikely to know each other and are therefore unlikely to have pre-existing ties. It is expected, therefore, that there will be more ties than would be expected by chance between participants of the same gender, educational background, similar educational background, in similar educational roles (e.g., principals), and with similar years of experience.

> P3: Shared personal and professional attributes (homophily) and differences in experience (heterophily) will increase the likelihood of a network tie.

Research Context

In the spring of 2013, The Friday Institute launched the MOOC-Ed Initiative (mooc-ed.org) to explore the potential of delivering personalized, high-quality professional development to educators at scale (Kleiman et al., 2013). In collaboration with the Alliance for Excellent Education, launched this initiative with a 6-week pilot course called Planning for the Digital Learning Transition in K-12 Schools (DLT), which was offered again in September 2013. This course was designed to help school and district leaders plan and implement K-12 digital learning initiatives. A second course, Mathematics Learning Trajectories: Equipartitioning (EQP), ran in August 2013. It introduced elementary- and middle-grades educators to learning trajectories as a framework for interpreting and implementing the Common Core State Standards. Among the core design principles of MOOC-Eds are collaboration and peer-supported learning. Courses combine Google Course Builder with Vanilla Forums and Google Hangouts on Air to facilitate these learning activities.

Data Collection

To address the above research questions, data came from two primary sources.

MOOC-Ed registration form. All participants complete a registration form for each MOOC-Ed course. The registration form consists of self-reported demographic data, including information related to their professional role and work setting, years of experience in education, and personal learning goals.

MOOC-Ed discussion forums. All peer interaction, including peer discussion, feedback, and reactions (e.g., likes), take place within the forum area of MOOC-Eds, which are powered by Vanilla Forums. To build peer support networks for network analyses, a MySQL file was downloaded for the two fall DLT and EQP courses. Separate database tables containing postings and comments were joined, or combined, to create a single network edge list (e.g., who interacted with who), which included participant IDs, timestamps, discussion text and other attributes. These data are merged with participant information from registration forms to create a single network analysis data file containing both peer interaction and participant attributes for qualitative coding and later import into SNA software. Because of the specific focus on peer supported learning, postings to or from course facilitators and staff were removed from the data set. Finally, analyses described below exclude more passive forms of interactions (i.e., read and reaction logs), and include only postings among peers.

Data Analysis

This study employed a mixed-methods approach that uses both SNA with qualitative methods to address the proposed research questions. SNA is a research methodology that seeks to identify underlying patterns of social relations based on the way actors are connected with each other (Scott, 2000; Wasserman & Faust, 1994). Specifically, SNA involves network metrics at the global level (e.g., density, reciprocity, degree distribution) and the individual level (e.g., centrality, node degree). In this study, SNA was used to measure and visualize patterns of interaction. *NodeXL*, a freely available template for Microsoft Excel, was used to calculate basic SNA metrics and create visualizations. In addition, two specialized network techniques were employed to address the first two research questions: blockmodeling and exponential random graph models (ERGMs).

To further examine patterns of peer support, actors in the network were categorized into distinct mutually exclusive partitions using the core-periphery and regular equivalence functions of UCINET. The former used the CORR algorithm to divide the network into actors that are part of a densely connected subgroup, or "core", from those that are part of the sparsely connected periphery (S. P. Borgatti, Everett, & Freeman, 2002). The latter employs the REGE algorithm to partition actors in the network based on the similarity of their ties to others with similar ties. On the importance of regular equivalence, Hanneman and Riddle (2005) note that "it provides a method for identifying "roles" from the patterns of ties present in a network, rather than relying solely on the attributes of actors to define social roles." In essence, blockmodeling provides a systematic way for categorizing educators based on the ways in which they interacted with peers.

The exponential family of random graph models (ERGM; also known as p* models) provide a statistical approach to network modeling that addresses the complex dependencies within networks. ERGMs were used to model the effects of individual and network attributes on support ties formed between participants. ERGMs predict network ties and determine the statistical likelihood of a given network structure, based on an assumed dependency structure, the attributes of the individuals (e.g., gender, popularity, location, previous ties) and prior states of the network. This study followed the procedure for constructing ERMGs described by Robins et al. (2007) and used statnet, an open-source suite of software packages for R to perform this modeling (Handcock, Hunter, Butts, Goodreau, & Morris, 2008). One common problem with model specification, known as degeneracy, is that parameter estimates can produce networks that are implausible (Snijders, 2011). To prevent model degeneracy, this study used the fixed version of the geometrically weighted terms for popularity spread (gwidegree) and transitivity (gwesp), with lambda set to one (Hunter, 2007; Robins et al., 2007). One limitation of this study is that models that incorporated parameters to assess transitivity, even geometrically weighted ones, still resulted in degeneracy and as a result this relational mechanism could not be modeled.

Finally, this study adopted the interaction analysis model (IAM) to assess the extent to which the interactions among educators resulted in the co-construction of knowledge (Gunawardena, Lowe, & Anderson, 1997). Two independent coders participated in a training session in which they were introduced to the content analysis coding scheme, and an initial codebook with examples from the literature. The session consisted of joint coding by the two coders and the lead author and involved independently coding and then discussing a subset of discussion threads selected by stratified random sampling based on length of discussion threads. All discussions were coded by the two primary coders, and in cases of disagreement, the third coder would assign a code. Discussions in which two out of three coders could not agree were excluded from the analysis. In total, 655 (40% of total) peer postings from DLT, and 232 (31%) from EQP were included in the analysis.

Findings

RQ 1. Patterns of Peer Support

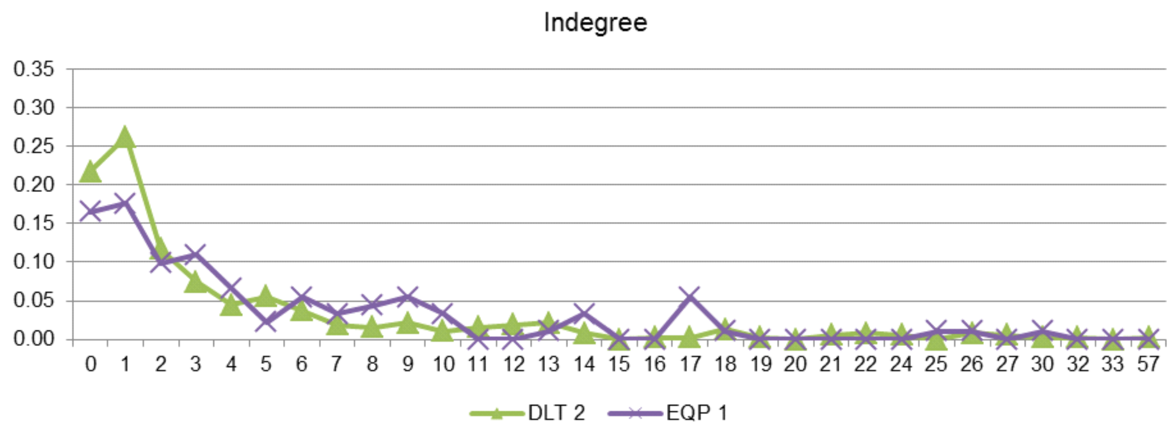
Network level statistics provide an overall description of the social network in terms of edge counts and network density, as well as the average measures of actor centrality and reciprocity. Table 1 provides a summary of these measures. As would be expected, the number of replies to peer postings (edges) increases with the number of educators in the network (vertices). Also as expected, graph density, that is, number of unique edges out of all possible edges, decreases in MOOCs with more educators as the number of possible edges increases exponentially with number of vertices. On average, DLT participants had ties to fewer peers as evidenced by both the average edge weight and in/outdegrees.

Table 1

Overall Network Measures for each MOOC-Ed

Network metrics	DLT	EQP
Vertices	377	91
Unique edges	1420	361
Edges with duplicates	360	370
Total edges	1780	731
Edge weight avg.	1.29	1.69
Reciprocated vertex pair ratio	0.15	0.15
Reciprocated edge ratio	0.26	0.26
Graph density	0.01	0.06
In/outdegree avg.	4.20	5.44
In/outdegree median	2	3
Indegree range	0-57	0-30
Outdegree range	0-41	0-37

Aside from these differences, some basic patterns can be identified across both MOOC-Eds. Measures of network reciprocity, for example, are fairly similar across the two MOOC-Eds, despite the size and varied composition of educators in each network. Also, both MOOC-Eds demonstrate similar patterns in the distribution of in/outdegree. As illustrated in Figure 1, the majority of educators had support ties with three or fewer peers. There were, however, several individuals in each course with a disproportionate number of ties compared to their peers. These “core” educators will be discussed in more detail below. Finally, the edge weight measure also demonstrates that most ties between educators consisted of a single communication and a general tendency for an individual’s responses to be distributed evenly among peers.



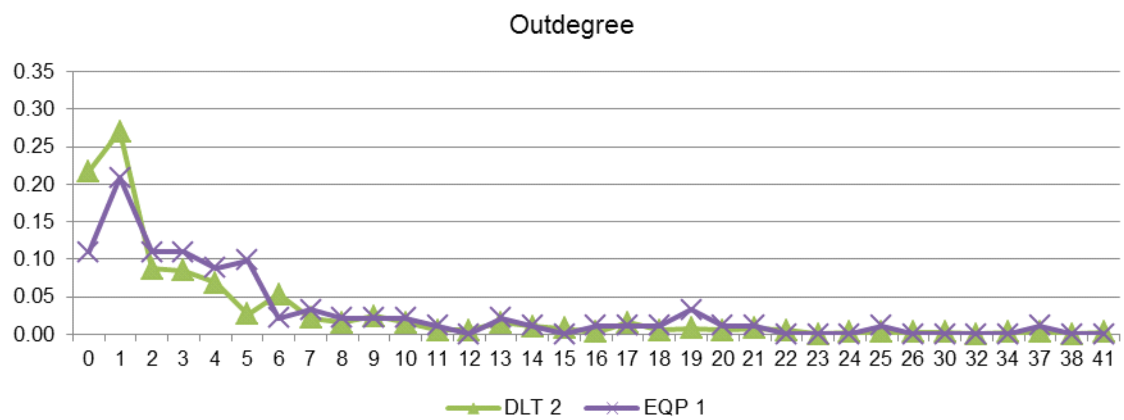


Figure 1. Proportion of outdegree distribution.

Figure 2 illustrates the combined results of these two partitions for the DTL peer support network. Solid discs represent educators identified as core to the network, while circles represent those on the periphery. In addition, all educators are blocked off into the following four simplified categories identified through blockmodel analysis: 1) Reciprocators – educators who participated in at least one mutual exchange as illustrated by the double-arrowed orange line connecting two educators, 2) Networkers – educators who were both the recipients and givers of support, though not with the same individuals, 3) Broadcasters – educators who initiated a discussion thread, but neither reciprocated with those who replied, nor posted to threads initiated by others, and 4) The Invisible – educators who responded to the postings of peers, but received no responses in return. As illustrated by the size of the block in Figure 2 and Table 2, Reciprocators made up the largest proportion of educators in both courses, and nearly all those identified as core to the network belonged to this group.

Table 2

Percentages of Educators in CORR and REGE Partitions

	DLT	EQP
Core-Periphery		
Core	13%	21%
Periphery	87%	79%
Regular equivalence		
Reciprocators	34%	36%
Networkers	23%	36%
Broadcasters	22%	11%
The Invisible	22%	16%

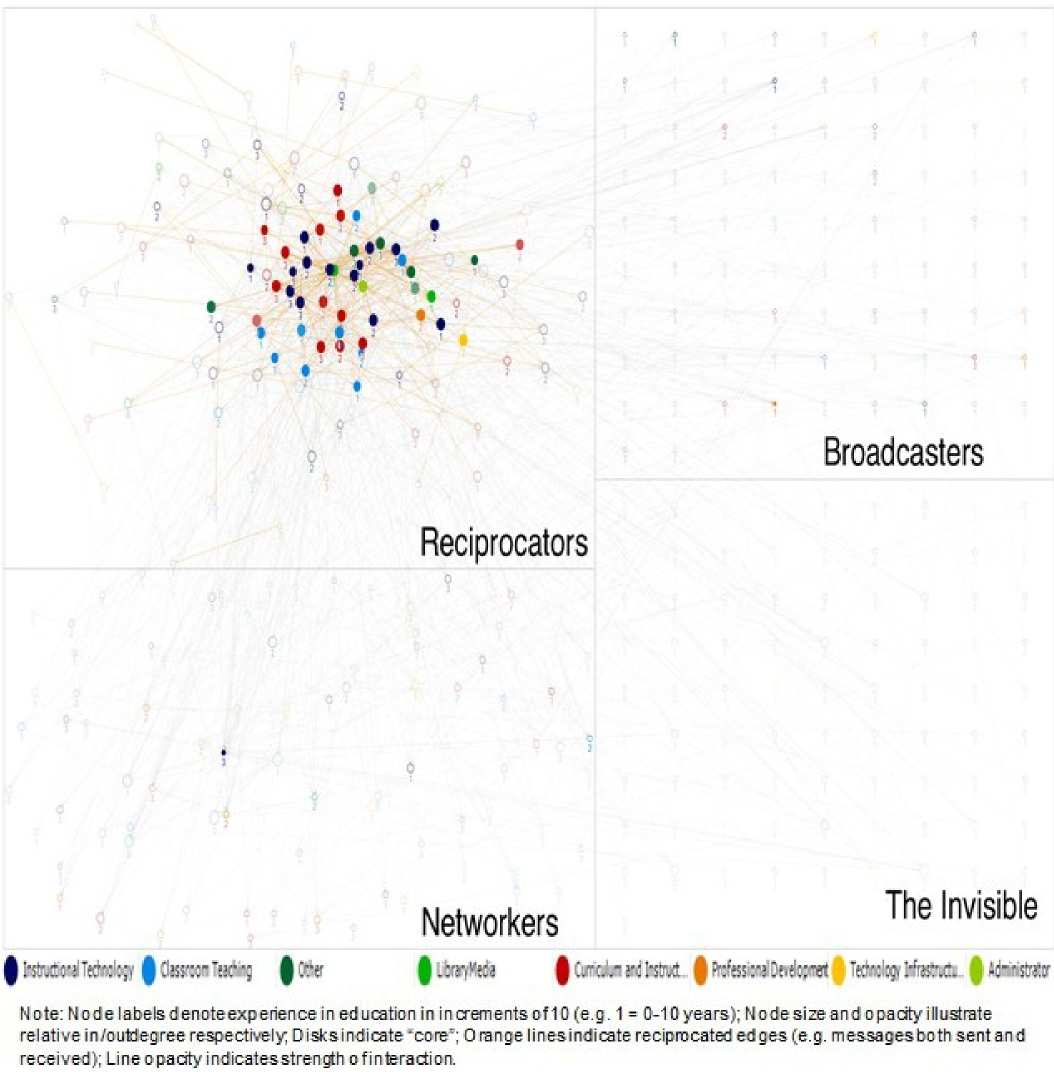


Figure 2. Sociogram of DLT peer-support network illustrating core-periphery and REGE partitions.

RQ 2. Mechanisms of Peer Support

ERGM estimation results for the two MOOCs are summarized in Table 3 and show the coefficients associated with each parameter, as well as the standard error. Similar to logistic regression, which predicts a binary variable from a number of predictor variables, ERGMs predict the presence of a network tie from several parameters, with estimates indicating the importance of each to the presence of a tie (Lusher, Koskinen, & Robins, 2012). Estimated coefficients can be thus explained in terms similar to logistic regression. Positive significant coefficients indicate that the corresponding parameters in the observed network (e.g., ties between educators with the same role), controlling for all other parameters in the model, occur more than would be expected by chance, thus increasing the likelihood that a tie will occur, and vice-versa for negative coefficients. Finally, the edges term in the model is equivalent to the number of ties in the observed network and serves the equivalent function of the y-intercept in linear regression (Morris, Handcock, & Hunter, 2008).

For all models and across both courses, the comparatively large significant parameter coefficient for reciprocity indicates a strong effect and suggests that educators are considerably more likely to respond to a peer posting if they have received a prior response from that same peer. The large significant negative coefficient for popularity spread is a little less intuitive to interpret, but Lusher (2012) explains that a large, negative popularity spread, as in this case, indicates that most actors have similar levels of popularity and that the network is not centralized on indegree. Another way to interpret this is that each response an educator receives significantly decreases the probability that an educator will receive an additional response.

Table 3

Summary of ERGM Model, Estimates and SE

	DLT		EQP	
	Estimate	*SE*	Estimate	*SE*
Baseline (Edges)	-4.50***	0.08	-2.05***	0.16
Structural mechanisms				
Reciprocity	3.43***	0.09	1.80***	0.17
Popularity spread	-3.33***	0.09	-3.38***	0.19
Assortative mechanisms				
Role homophily	0.17**	0.06	-0.01	0.11
Role nodefactor[a]				
Administrator	-0.01	0.06	-0.25	0.14
Curriculum	0.08*	0.00	-0.32**	0.11
Library/Media	0.21***	0.05	--	--
Instructional tech	0.06*	0.03	--	--
Teacher educator	--	--	-0.08	0.06
Tech infrastructure	-0.07	0.07	--	--
Prof. development	0.00	0.05	-0.20*	0.11
Other	0.11**	0.04	-0.05	0.07
Homophily by grade	0.17***	0.04	0.03	0.08
Homophily by gender	0.08*	0.04	0.04	0.04
Experience difference	0.04	0.04	-0.02	0.07
Experience nodefactor[b]				
11-20	-0.01	0.03	0.12	0.07
More than 20	-0.04	0.03	-0.03	0.06
Desire to connect	-0.04	0.03	-0.10	0.09
Proximity mechanisms				
State or country	0.71***	0.08	0.06	0.18
Geographical region	0.05	0.06	-0.18	0.11
Group assignment	0.54***	0.05	--	--
AIC	14847		3353	

Notes. * $p < .05$. ** $p < .01$. ***$p < .001$.
[a] Classroom Teaching serves as the comparison group
[b] Educators with 0-10 Years of Experience in Education serve as comparison group

Regarding assortative mechanisms, results for homophily by role indicate a positive significant effect in the DLT MOOC, but no effect in the EQP course. This indicates that, in general, if educators shared similar roles it increased the likelihood of a support tie in the former course but not in the latter. When homophily was examined by grade levels worked with (e.g., elementary, high school), as well as by gender, the effects were again positive and significant only in the DLT course, indicating that if two educators worked at the same school level, or shared the same gender, it also increased the likelihood of a tie. A heterophily terms was also added to examine educators' years of experience;

however, the presence of ties between educators with different years of experience found in the observed network were no more than would be expected by chance.

In addition to homophily and heterophily, this model also examined the extent to which educators' professional role, experience, or desire to connect increased the likelihood they would have a support tie with peers in the network, either on the giving or receiving end. The findings suggest that across both MOOCs, one's professional role significantly increased or decreased the likelihood they would form a support tie when compared to classroom teachers. Regarding years of experience and a desire to connect, however, no significant effects were found, suggesting that in both cases, educators with more experience or who expressed a desire to connect were more likely to be involved in a support tie.

Finally, findings for two of the three proximity mechanisms were significant in DLT, but not in EQP. In these two courses, this indicates that educators were more likely to respond to a peer if their school or work location was in the same U.S. state or country, even beyond the effect of being assigned to discussion groups by the first letter of their state or county in DLT. This did not carry over to geographical regions, however. That is, being located in the southern states of Georgia, North Carolina, and South Carolina did not increase the likelihood these educators would respond to each other's postings.

RQ 3. Co-Construction of Knowledge

Results of the interaction analysis model provide insight into the extent to which discussion resulted in the co-construction of new knowledge. Coding classified each discussion thread into one of the following five categories according to the highest phase reached by the postings within that discussion.

> Phase 1 - Sharing and comparing. Further the discussion by providing observations, opinions or examples that support or extend prior statements.
>
> Phase 2 - Dissonance and inconsistency. Identify areas of disagreement or potential disagreement.
>
> Phase 3 - Negotiation and co-construction. Explore common ground, clarify intent, seek agreement or integrate ideas.
>
> Phase 4 - Testing and modification. Test ideas against prior information, research and/or data and proposed synthesis of ideas.
>
> Phase 5 - Summary, application and metacognition. Summarize agreements, describe applications of knowledge or acknowledge changes in understanding.

The data, shown in Figure 3, display the proportions of total discussions by the highest phase reached. In both courses, that vast majority of discussions analyzed either remained at the level of sharing and comparing information, or entered a process in which dissonance was recognized among peers and process of negotiation or construction began to take place. However, few discussions moved beyond Phase 3.

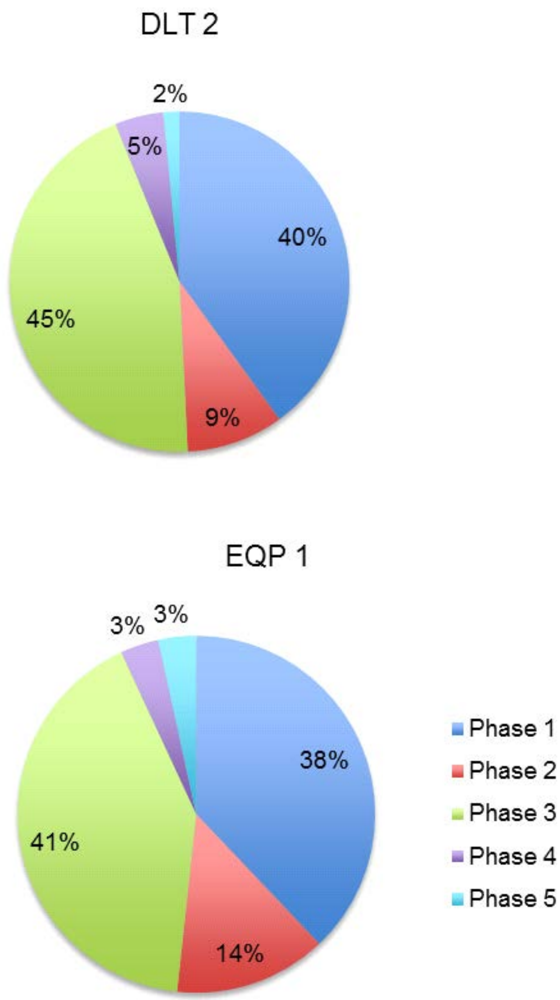


Figure 3. Highest phase of knowledge construction reached by discussion threads.

Discussion

Wenger, Trayner, and De Laat (2011) describe social networks as "a set of relations, interactions, and connections... with affordances for learning, such as information flows, helpful linkages, joint problem solving, and knowledge creation" (p. 9). This study demonstrates that even with technology as basic as a discussion forum, MOOCs can be leveraged to foster these networks and facilitate peer-supported learning that results in the process of knowledge construction. However, mirroring emerging MOOC findings on steep declines in participation and course completion, both peer networks demonstrate similar drop-offs in the extent to which educators leveraged their peers.

Findings on patterns of peer interaction are characteristic of online social networks in general, in which core-periphery structures, power-law degree distributions, and the prevalence of weak-ties are common (Aviv, Erlich, & Ravid, 2007; Butts, 2008; C. R. Jones, Ferreday, & Hodgson, 2008). In terms of regular equivalence partitions, these results are comparable to the findings by Wasko, Teigland, and Faraj (2009) in two online professional networks of practice. The authors reported that half of the network consisted of “outsiders” who did not receive responses, and “seekers” who received responses but did not reciprocate or pay it forward. Blockmodel analysis, however, failed to fully capture the nuances in patterning of ties. For example, while Broadcasters provided no response to their peers, many received responses from a large number of peers. In contrast, The Invisible, who despite receiving no communications from their peers, consisted of many educators who provided a disproportionately large number of responses. Finally, both Reciprocators and Networkers often skewed either towards a greater indegree or outdegree, that is, they tended to receive more support than they provided, and vice-versa.

Beyond describing the patterns of peer interaction, this study examined mechanisms that shape the structure of these networks. Several theoretical propositions drawn from the literature on social networks, online learning, and social learning perspectives were examined through ERGM analysis. Across both MOOCs, significant effects were found for the relational mechanism of reciprocity, but not for a popularity effect. Of specific interest to this study was the impact of educators’ professional roles and years of experience. Drawing from the communities of practice perspective on social learning (Wenger et al., 2011; Wenger, 1999) it was anticipated that educators in similar professional roles and settings might be more likely to interact based on a shared “domain of practice”, and that less experienced educators might seek out more experienced peers for support. However, evidence for homophily and proximity were only identified in the larger DLT course, and there was no evidence of a mentoring effect in either. The lack of homophily in EQP may be the result of the MOOC-Ed’s unique content focus, creating a specific shared domain of practice while also encouraging interaction across grade levels, negating a need to seek out others in similar roles and settings. The absence of a mentoring effect in both courses, however, may stem from the lack of what Baker-Doyle and Yoon (2010) refer to as “expertise transparency”. That is, with limited information about their peers gleaned from postings or the small handful of completed participant profiles, it may be difficult to identify experts in the MOOC. In a case study of online communities for educators, Booth (2011) suggested that network size and detailed member profiles may have played a role in cultivating knowledge sharing among educators.

Finally, findings on knowledge construction demonstrated that over half of the discussions in both courses moved beyond sharing information and statements of agreement and entered a process of dissonance, negotiation and co-construction of knowledge, but seldom moved beyond this phase in which new knowledge was tested or applied. These findings echo difficulties in promoting knowledge construction online found by several researchers (Aviv et al., 2003; Heo et al., 2010; Hou & Wu, 2011; Pena-Shaff & Nicholls, 2004). For instance, Gunawardena et al. (1997) found that interactions among conference participants as part of distance education online debate seldom moved beyond the lower phases of sharing and comparing information. Zheng and Spires (2012) found that communication between students in a graduate level education course primarily remained at the lower level Phase I stage of sharing and comparing information despite active facilitation by the instructor. It is tempting to conclude that because so few discussions reached Phase 5, there was little application of shared knowledge to the problems or issues under discussion. However, this may be the result of our interpretation of the IAM coding scheme. Practical strategies and solutions to problems or issues raised during discussion were frequently shared, but these were often coded as Phase I because they did not arise through an explicit process of negotiation and co-construction of new knowledge. Johnson et al. (2008) noted that interaction must be intentionally designed into the learning context or it is unlikely to result spontaneously. The authors of this paper contend that the same is also true for fostering knowledge construction in MOOCs.

The findings from this study also suggest several design implications for future MOOC-Eds. Kraut and Resnick (2012) have proposed numerous design claims intended to encourage contributions and exchanges in online communities, but several stand out for consideration for the design of future MOOC-Eds. Design claim 5 states that simple requests for contributions rather than lengthy or more complex ones lead to greater compliance among those who do not care strongly about contributing. In addition to the more substantive contributions such as reflective discussion prompts or detailed peer feedback, MOOC-Eds should consider providing discussion opportunities which request quick, practical information that would be of use to other educators in the community, such as requests embedded and directly relevant to content and resources provided throughout the course. Design claim 11 also states that participants are more likely to respond to the requests of others, such as with feedback on discussion postings, when they come from others who are familiar to them or more closely resemble them. One simple approach to doing so would be to request participants make public information about their professional experience and personal background gathered from the registration process via their personal profiles so peers can more easily identify each other's professional roles, work context, and experience.

Finally, beyond just facilitating the quantity of exchanges, it is important to ensure the quality of interaction is contributing value to the community. While "quality" interaction can be defined in a variety of ways, Pear and Crone-Todd (2002) point out that meaningful interaction is not just sharing opinions and information, but should stimulate the learners' intellectual curiosity. Likewise, social constructivists do not maintain that all conversation and discussion occurring anywhere anytime are meaningful for learning, but that discussion should be directly relevant to his/her real life and take place within a culture similar to an applied setting (Brown, Collins, & Duguid, 1989). In order to foster meaningful dialogue, Pear and Crone-Todd (2002) suggest providing guidelines for interaction, while Rovai (2001) stresses the importance of setting expectations for participation, whether in a formal social context such as an online course, or an informal context such as an online community of practice. Future MOOC-Eds will likely need to better scaffold social learning processes in order to fully leverage the potential of peer-supported learning.

Although the scope of this study was naturally constrained by funding and time, these limitations present several avenues for future research. Naturally, generalizations cannot be drawn based on two MOOCs from a single department at a university. Ideally, this study would have been comprised of numerous courses across multiple platforms to compare the networks that emerged and test the robustness of ERGMs used to model peer support mechanisms. In addition, the simplified model presented in this study was designed to examine a few theoretical propositions based on available data in aggregated form. Howison, Wiggins, and Crowston (2011) note that aggregate networks fail to capture temporal dynamics, and that replies in online threaded messages are often not a valid measure of the construct of interest, in this case “peer support”. A more complete model would have included additional relations, such as posts “read” or “liked”, as well as attributes of the postings such as timing, strength, and especially content of the postings. Finally, Edwards (2010) notes a need for a more systematic integration of SNA and content analysis, for “whilst we may divorce form from content, or structure from agency for analytic purposes, it is in that ‘messiness’ of actual social networks that they are always combined...”

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THE INTERNATIONAL REVIEW OF RESEARCH IN OPEN AND DISTANCE LEARNING

Making 'MOOCs': The Construction of a New Digital Higher Education within News Media Discourse

  

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Abstract

One notable 'disruptive' impact of massive open online courses (MOOCs) has been an increased public discussion of online education. While much debate over the potential and challenges of MOOCs has taken place online confined largely to niche communities of practitioners and advocates, the rise of corporate 'xMOOC' ventures such as Coursera, edX and Udacity has prompted popular mass media interest at levels not seen with previous educational innovations. This article addresses this important societal outcome of the recent emergence of MOOCs as an educational form by examining the popular discursive construction of MOOCs over the past 24 months within mainstream news media sources in United States, Australia and the UK. In particular, we provide a critical account of what has been an important phase in the history of educational technology—detailing a period when popular discussion of MOOCs has far outweighed actual use/participation. We argue that a critical analysis of MOOC discourse throughout the past two years highlights broader societal struggles over education and digital technology—capturing a significant moment before these debates subside with the anticipated normalization and assimilation of MOOCs into educational practice. This analysis also sheds light on the influences underpinning how many people perceive MOOCs thereby leading to a better understanding of acceptance/adoption and rejection/resistance amongst various professional and popular publics.

Keywords: MOOC; higher education; education reform; elearning; discourse; news media

Introduction

One of the most notable 'disruptive' impacts of massive open online courses (MOOCs) to date has been the increased public discussion of online education and e-learning. Of course, much debate over the rights and wrongs of MOOCs has taken place online (through blogs, Twitter and other social media platforms), but thereby confined largely to niche communities of likeminded education technology practitioners and advocates. However, the rise of corporate 'xMOOC' ventures such as Coursera, edX and Udacity has prompted popular mass media interest at levels not seen with previous educational innovations. Indeed, perhaps the most tangible impact of MOOCs to date has been their stimulation of an unprecedented volume *and* urgency of debate about higher education in the digital age.

This article (and the broader MRI-funded project that it provides a 'first glimpse' of) addresses this important societal outcome of the recent emergence of MOOCs as an educational form—examining the popular discursive construction of MOOCs over the past 24 months within mainstream news media sources. Such an approach provides a counterpoint to many of the other research articles in this Special Issue. In particular, this article provides a critical account of what has been an important phase in the history of educational technology—detailing a period when popular discussion of MOOCs has far outweighed actual use/participation. As such, a critical analysis of MOOC discourse throughout the past two years highlights broader societal struggles over education and digital technology—capturing a significant moment before these debates subside with the anticipated normalization and assimilation of MOOC-like online education, in whatever form, into educational practice. This analysis also has a practical benefit of shedding light on the influences underpinning how many people perceive MOOCs—leading to a better understanding of acceptance/adoption and rejection/resistance amongst various professional and popular publics.

In terms of theoretical approach, this project is situated within the tradition of critical discourse analysis (Fairclough, 2003), and is therefore concerned primarily with the ways in which the discourses around MOOCs reproduce and/or disrupt social and political inequalities within higher education. This approach is well-suited to testing the ideologies and values that have surrounded the recent rise of MOOCs—especially in terms of claims related to: the democratizing of educational opportunity; the challenging of institutional monopolies within higher education; and the benefits/limitations of a diversity of educational provision. As Taylor (2004) argues, taking this approach is of particular value in documenting multiple and competing discourses within education, in highlighting marginalized and hybrid discourses, and in documenting discursive shifts over time. Given the fast-changing and complex nature of the development of MOOCs over the past few years (e.g., from the connectivist model of the 'cMOOC' to the corporate and institutionally-focused model of 'xMOOCs'), a discourse analysis perspective can provide a much-needed socio-political analysis to the prevailing claims and counter-claims currently surrounding this area of educational activity.

Research Questions

Against this background, the remainder of this article will explore the following research questions:

1. How have MOOCs been interpreted in popular news discourses?

2. What meanings and understandings of education and/or technology have been conveyed through these various portrayals of MOOCs?

3. In whose interests do these portrayals of MOOCs work? What issues and concerns are less prominently portrayed?

Research Methods

The article adopts a discourse analysis approach to investigating these questions – drawing on established methodologies from social linguistics and the social sciences that have also begun to be used increasingly in educational research (see Rogers et al., 2005 for an overview). First, a large-scale corpus of text was established encompassing news media stories produced between January 2012 and December 2013 in the following two areas of English language discourse production:

	Representative sources
Popular news-media	*New York Times*; *Washington Post*; *Times/ Sunday Times* (UK); *Guardian/Observer* (UK); *The Australian*; *The Age* (Australia)
Educational news-media	*Higher Education Chronicle*; *Times Higher Education*; *Education Week*

The six popular news-media sources were selected deliberately to include the 'newspapers of record' from the US (New York Times), UK (Times) and Australia (Australian), alongside corresponding national titles in each country which have also focused on educational and technology issues (Washington Post, Guardian, Age)[i]. Similarly the three specialist educational news-media titles were selected due to their long-standing reputation as authoritative sources on higher education (Chronicle, Times Higher Education), and their sustained featuring of MOOC-related reports over the past three years (Education Week). Interrogations of these sources through the Factiva databases with the search terms 'MOOC or Udacity or edX or Coursera' returned 457 different articles (see Figure 1 for a breakdown of these data by month and country of origin). All text was collated and categorized using the N*VIVO qualitative data analysis application.

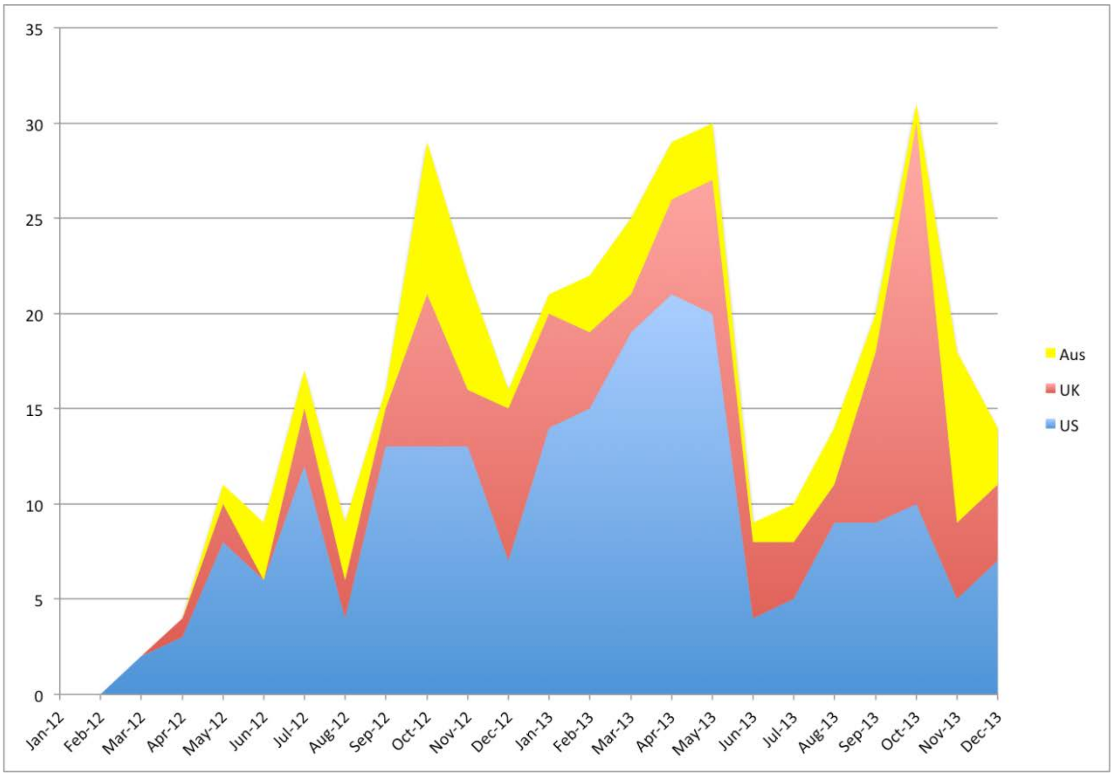

Figure 1. Production of news media articles by month/year and country of publication.

The initial phase of data analysis reported upon in this article used a frame analysis of MOOC discourses (Gerhards, 1995; Goffman, 1975; MacLachlan & Reid, 1994). This aimed to analyze the 'tone' of the media discourse on MOOCs and 'sketch' how MOOC issues are viewed. The data reported on in this article relate to two elements of each newspaper article. First, is the headline attached to the article—usually written by a newspaper's sub-editor and intended to provide 'initial summaries of new texts and foreground what the producer regards as most relevant and of maximum interest or appeal to readers' (Brookes, 1995, p. 467). In this sense, 'headlines help readers construct an ideological approach to the content of the article ... provid[ing] the dominant image of a given event and the way the event is apt to be stored in the mind of readers' (Johnson & Avery 1999, p. 452). In total 371 headlines were specifically related to MOOCs (as opposed to generic titles such as 'News In Brief') and coded accordingly. Second, is the initial orientating description offered within the main text of the news article (if at all) of what a 'MOOC' is. In total, 281 such descriptions were identified and coded accordingly. These were typically one or two lines, with an average of 14.53 words per excerpt. Focusing on these two integral elements of each article allows us to identify two important meaning making functions—the 'what is?' question (contained in the in-text description) and the 'so what?' question (contained within the headline).

Our analysis of these texts was both quantitative and qualitative in nature, thereby aiming to identify the overall patterns of how MOOCs have been interpreted by different sources. Particular attention was paid to identifying patterns between type of discourse and the characteristics of the sources involved (i.e., type of publication, institutions/individuals that are represented and so on.). A further aim of this analysis was to cross-tabulate specific discursive themes/concerns with different types of institution/stakeholder/country—thereby beginning to explore the patterning of MOOC discourses across different sub-groups and contexts.

Research Findings

The analysis and coding of the headline and definition texts resulted in 14 distinct themes—the nature and prevalence of which is described in Table 1 and below.

Table 1

Issues and Meanings Associated with MOOCs within the Headlines and In-Text Descriptions of News Media Articles

Theme	Headlines	Descriptions	Total
Change	87	38	125
Free	28	79	107
Size and scale	39	63	102
High-profile elite universities	26	39	65
Higher education marketplace	39	11	50
Pedagogy	16	29	45
Global/ local phenomenon	24	19	43
Assessment	28	12	40
Teachers	19	16	35
Technology	9	17	26
Business and economic aspects	16	4	20
Content	17	1	18
Learning	9	7	16
Students	8	7	15

Prominent Issues and Meanings

As the data in Table 1 show, the most prevalent definitions and justifications related to the following four themes: i) MOOCs as a source of change; ii) MOOCs as a source of free education; iii) the size and scale of MOOC programs; and iv) the MOOCs of high-profile elite universities.

The most prevalent meaning within the data was that of a vague sense of inevitable, substantial **'change'** (n=125). MOOCs were described as a 'digital change agent' (Chronicle of HE, 4.3.2013) and source of 'creative destruction' (Washington Post, 20.5.2013). A key theme here was disruption of the established order—'the education world has been thrown into disarray' (Sunday Times, 1.12.2013), with MOOCs 'disrupting centuries-old models' (Chronicle of Higher Education, 28.10.2013). These were courses that marked a new educational direction—'path breaking' (Chronicle of HE, 25.3.2013) and representing 'learning's new path' (Australian, 17.8.2013). The momentum of these changes was described in forceful terms as a 'revolution' (New York Times, 16.5.2012), 'juggernaut' (Australian, 7.11.2012) and 'phenomenon' (Washington Post, 29.8.2013). Throughout all these descriptions was an unspecified inference that MOOCs were altering substantially the structures of higher education. The MOOC was announced as 'game-changing' (Times Higher Ed, 20.12.2012), and as a 'game-changer' (New York Times, 17.7.2012) that 'changes the game' (Age, 5.6.2012).

The importance of these changes was sometimes described as marking a distinctive point in time – signifying 'higher education in the digital age' (Times Higher Ed, 6.6.2013), or an 'era of free courses' (Chronicle of HE, 1.10.2012). As the New York Times (4.11.2012) put it, 2012 was 'The Year of the MOOC'. On occasion such claims of history-in-the-making were tempered with a knowing nod towards the prevailing hyperbole. The topic was acknowledged as 'the current buzz in higher education' (New York Times, 15.10.2013); a 'bandwagon' (Chronicle of HE, 3.9.2012) and source of 'irrational exuberance' (Washington Post, 27.1.2013). As this awkwardly self-aware description put it,

> MOOCs. It sounds like a hipster street wear brand, but the acronym stands for massive online open courses—and they are flavour of the month. Just like new street wear, they are seen as the next big thing that everyone will want to have. (Age, 28.8.2012)

Beyond this apparent timeliness, the imagined origins of the change associated with MOOCs were divided along two distinct lines. Crudely, the origin stories associated with MOOCs followed narratives concerned with either 'science' or 'nature'. In the former sense were portrayals of MOOCs as a product of science-like development and innovation. MOOCs were described on numerous occasions as 'experiments'—that is, 'an important new experiment in higher education' (Washington Post, 8.10.2013); 'somewhat experimental' (Australian, 6.3.2013); and 'radical experiments in higher education' (Times, 17.10.2012). These were 'wildly innovative offerings' (Washington Post, 10.05.2012) that stemmed from 'the soul of invention' (Chronicle of HE, 25.3.2013). Udacity was introduced as 'an internet platform created by two Stanford University scientists' (Times Higher Ed, 17.7.2012)—a feat of invention akin to other ambitious innovations in science and engineering—'from self-flying helicopters to classrooms of the future' (Chronicle of HE, 1.10.2012).

These stories of scientific invention and innovation were accompanied by contrasting construction of MOOCs as natural phenomena. Here, parallels were often drawn with forces of nature—a 'campus tsunami' (New York Times, 4.5.2012), 'an avalanche' (Guardian, 30.4.2013) and 'an online wave' (New York Times, 23.9.2013). The capacity of MOOCs for change and renewal was sometimes framed in material and elemental terms—'instruction for masses knocks down campus walls' (New York Times, 5.3.2012); 'MOOCs break the mould' (Australian, 20.2.2013); 'MOOCs knocking at the foundations' (Australian, 20.2.2013); or 'MOOCs Sends Shock Waves' (Chronicle of HE, 14.3.2013). On occasion, this association with nature was imagined in bestial rather than elemental terms. MOOCs were 'a new beast in the academy' (Times Higher Ed, 6.12.2012) and somewhat fancifully a 'disruptive dragon' (Times Higher Ed, 6.12.2012). The implication of such evolution was the eventual distinction of previous forms of education: "The MOOC is the latest stage in a series of technological changes that have made life easier for students and their teachers but have made the traditional lecture look ever more of an endangered species" (Times Higher Ed, 4.10.2012).

The second prominent meaning associated with MOOCs was the more uniformly expressed characteristic of being **'free'** (n=107). This oft-repeated term was clearly being used in a monetary rather than an emancipatory sense (i.e., 'free beer' rather than 'free spirit'). Thus the most prominent feature of the in-text descriptions (79 of the 281 coded descriptions) was the ostensibly no-cost nature of MOOCs. These were programs that offered university education of 'the kind once available only to students paying tens of thousands of dollars in tuition at places like Harvard and Stanford' (Chronicle of HE, 3.6.2013). In this spirit, MOOCs were presented as 'free education' (Guardian, 4.12.2012), 'a new kind of free class' (New York Times, 21.8.2012), and as an 'undergraduate-level courses without any fees' (Times, 17.7.2012). The concept of university-level education being offered to students 'at no charge' (Washington Post, 4.11.2012) was generally described in incredulous tones, but also on occasion as a logical development in financially constrained times. As one Washington Post (5.9.2013) headline put it, 'The Tuition is Too Damn High, Part IX: Will MOOCs save us?'.

As befits the opening word of the acronym, a third defining feature of MOOCs was their **size and scale** (n=102). Notable throughout the data was news media's continual attempts to synonymize the concept of 'massive'. Thus MOOCs were introduced as 'huge' (Chronicle of HE, 2.7.2012; Times, 20.6.2013); 'giant' (New York Times, 11.3.2013); 'mass' (Australian, 8.7.2012) and 'mega' (Chronicle of HE, 17.9.2012). This was education on a 'very large-scale' (Australian, 27.11.2012) and reaching 'a very large number of people' (Washington Post, 28.8.2013). Indeed, the exact quantification of this 'mass engagement' (Times Higher Ed, 18.10.2012) varied considerably between sources. The Chronicle of Higher Education (11.6.2012; 1.10.2012; 8.5.2013) was keen to talk about 'thousands of students'. On other occasions these numbers increased to 'tens of thousands of people' (Washington Post, 24.8.2013); 'courses with more than 100,000 people enrolled' (Chronicle of HE, 1.10.2012); and more specifically '150,000 students' (New York Times, 22.7.2012). Less precisely was talk of 'millions of learners around the world' (Washington Post, 3.5.2012), and even less probably estimates of 'opening higher education to hundreds of millions of people' (New York Times, 17.7.2012).

These increased volumes of learners were portrayed consistently as a vast—if not unlimited—expansion of what was previously a constrained process. MOOCs were celebrated for their 'unlimited capacity for enrolment' (Chronicle of HE, 22.10.2012) and 'unfettered' nature (Chronicle of HE, 8.8.2013). This expansion was typically associated with various economies of scale—facilitating courses that were somehow able to 'harness the power of their huge enrolments' (New York Times, 20.11.2012). In particular, descriptions in the mainstream newspapers highlighted the democratizing nature of MOOCs. As one New York Times (5.3.2012) article put it, 'welcome to the brave new world of Massive Open Online Courses—known as MOOCs—a tool for democratizing higher education'. These were courses 'open to all' (New York Times, 15.7.2013), 'freely available to anyone who wants to use them' (Guardian 23.10.2012), or at least 'anyone with an Internet connection' (New York Times 30.4.2013).

Another defining issue prominent throughout the data (n=65) was the notion that MOOCs were the province of **high-profile elite universities**. The MOOCs referred to within the majority of articles were being developed by 'leading unis' (Guardian, 18.6.2013); 'top universities' (New York Times, 18.4.2012; Times, 16.9.2013; Times Higher Ed, 17.7.2012); 'world-leading universities' (Age, 2.10.2012) and 'leading academic brands' (Washington Post, 4.5.2012). MOOCs were described as being the preserve of 'elite' (Washington Post, 2.5.2013; 4.11.2012; 7.2.2013); 'prestigious' (Times Higher Ed, 21.3.2013; 10.5.2012; Chronicle of HE, 18.6.2012); 'stellar' (Australian, 8.11.2013) and 'star' institutions (Times Higher Ed 20.12.2012; Chronicle of HE 5.11.2012). Despite their mass nature, MOOCs were certainly not the realm of the ordinary.

A recurring theme within US news media portrayals of this exceptionalism was the inference that the development of MOOCs was driven by elite American universities—as the Chronicle of HE (1.10.2012) put it, 'led by some of the nation's most prestigious research universities'. Alternatively, Australian news media were more likely to stress the involvement of Ivy League universities. Here, MOOCs were positioned as 'an online phenomenon emanating from the US's Ivy League' (Australian, 17.8.2013), with this specific association adding luster to online learning: 'online courses winning prestige—Ivy League lends knowledge' (Australian, 4.7.2012). This pride in the Ivy League was conveyed in a few US commentaries. Indeed, the Washington Post (10.5.2012) went as far as to equate MOOCs with recent social uprisings in north Africa and the Middle East—'what some have referred to as the "Ivy League Spring"'. Thus a telling distinction emerged in these descriptions between institutions that were 'top dogs' (Times Higher Ed, 20.9.2012) and 'big fish' (Times Higher Ed, 26.9.2013) as opposed to the 'small fry' (Times Higher Ed, 26.9.2013).

Peripheral Issues and Meanings

As can be seen from Table 1, a number of less prevalent meanings and issues were also apparent within the text corpus. First amongst these were a set of issues relating to the **higher education marketplace** (n=50) and competition between education providers. These descriptions tended to focus on the role of MOOCs in reordering the higher education marketplace. On one hand, universities' involvement in MOOCs was presented as a prerequisite for remaining a competitive higher education provider—as the Guardian (28.10.2012) put it, 'traditional universities have felt the need to cover their internet flank by offering courses online'. Conversely, MOOCs were contributing to an uncertain 'future in flux: the battle for the online market is just beginning' (Times, 17.10.2012). Flux or not, most of these stories described already successful universities extending their market reach. MOOCs were described as an additional opportunity for universities to extend their 'export strategy' (Australian, 1.8.2012) and 'expands slate of universities' (New York Times, 19.9.2012). Thus rather than disrupting the pre-existing market dynamics, MOOCs tended to be defined as augmenting rather than altering patterns of market success. As the Australian (6.6.2012) explained, 'MOOC is not a direct competitor. It is a new kind of product. It could become a second line of credential'. Similarly, as one UK newspaper described, 'for universities, MOOCs act like virtual shop windows to drive paying students through their doors' (Sunday Times, 1.12.2013). MOOCs were seen as offering an additional gateway into 'full' and more traditional forms of higher education—'taster' courses (Australian, 31.10.2012; 27.11.2013).

Second in terms of less prominent issues were those related to **pedagogy** (n=45). When pedagogic issues were evoked, the texts focused largely on the modes of delivery used in MOOC-based teaching and learning. Here MOOCs were most commonly described using the typical language of university tuition—that is, as 'online classes' (New York Times, 18.9.2013); the 'online lecture' (Washington Post, 2.5.2013); 'online tutorials' (Times, 8.9.2012); the 'virtual seminar' (Education Week, 6.2.2013). When not framing MOOCs in these familiar terms, articles and headlines were pointing to another defining pedagogic feature of MOOCs—the use of videos and quizzes—which allowed students to simply 'watch the videos and do the assignments' (Washington Post, 5.9.2013). The 'broadcast' nature of these pedagogies was expressed most starkly in this description from the Chronicle of HE (13.8.2012)—'one person can teach the whole world with a cheap webcam and an internet connection'. Tellingly, the pedagogic limitations of these forms of teaching and learning were rarely commented upon. As one atypical headline from the Times Higher Ed (18.10.2012) questioned: 'nice publicity, shame about the pedagogy'.

Third, were occasionally perceived tensions between MOOCs as a **global or local phenomenon** (n=43). In the former sense were declarations of MOOCs as 'the university of the world' (Australian, 5.11.2012), with a 'truly international' (Age, 23.10.2012) reach 'around the world' (Washington Post, 19.10.2012; Chronicle of HE, 1.10.2012; Age, 2.10.2012; Washington Post, 24.8.2013). In contrast, were more nationally-bounded descriptions of MOOCs. These stories featured talk of ‘British MOOCs’ (Times Higher Ed, 21.3.2013), a ‘Hong Kong MOOC’ (Chronicle of HE, 22.4.2013) and the US-centric notion of ‘teaching to the world from Central New Jersey’ (Chronicle of HE, 3.9.2012). Indeed, in this latter sense the Times Higher Ed (4.4.2012) reported ‘doubts about uncollaborative and 'imperialist' US platforms’.

Nearly as much concern was shown over matters of **assessment** (n=40), particularly with regards to matters of credentialing, grading, qualifications and measuring quality. One primary concern here was how MOOCs fitted with the traditional university forms of credentialization, with questions raised over ‘campus credit for online classes’ (New York Times, 12.3.2013). Two specific ‘issues’ along these lines recurred within the data. Firstly, were issues of grading and assessment, with questions raised over proposals for some MOOCs to use automated grading software, or ‘a digital auto-grader’ as the Chronicle of HE (3.9.2012) described it. These concerns were encapsulated in the faux-alarmist New York Times (12.4.2013) headline ‘That dastardly computer gave my essay a D!’. A second area of consternation was the prospect of universities awarding certificates for a fee—‘online classes will grant credentials, for a fee’ (Washington Post, 9.1.2013), and the associated risks of online test-takers being able to succeed fraudulently—‘cheating no credit to open course students’ (Age, 28.8.2012).

Teachers who were involved in the development and running of MOOCs—although featured only in 35 headlines and descriptions—were portrayed generally in exceptional terms. These were ‘dynamic, learned professors’ (Chronicle of HE, 3.6.2013); ‘star professors’ (Chronicle of HE, 18.6.2012); and ‘the world's most esteemed professors’ (Australian, 5.11.2012). MOOCs therefore offered students the opportunity to experience a ‘daily dose of demigod’ (Times Higher Ed, 3.10.2013), or even a chance to engage with celebrity—‘some professors becoming the Kim Kardashians of the academic world’ (Australian, 5.11.2013). In contrast, and as one might expect, dissenting teachers were portrayed in less exceptional terms—that is, ‘scholars sound the alert from the 'dark side' of tech innovation’ (Chronicle of HE, 8.5.2013); ‘a chance to get rid of duff scholars’ (Times Higher Ed, 24.10.2013); ‘MOOCs' revolution spooks academics’ (Times, 27.9.2013) and a ‘faculty backlash’ (Chronicle of HE, 6.5.2013). Notably, teachers not engaging fully with MOOCs tended not to be ‘professors’, but scholars, academics and faculty.

The actual **technology** of MOOCs was mentioned only occasionally (n=26), and then in vague terms. MOOCs were defined loosely as an ‘education technology platform’ (Australian 31.7.2013) or ‘higher education by computer, iPad or smartphone’ (Australian, 1.8.2012). The technology of MOOCs was most often defined in association with more familiar digital platforms. Thus MOOCs were defined as ‘the iTunes of academe’ (Australian, 31.7.2013) and ‘the YouTube of online learning’ (New York Times, 11.9.2013). As the Chronicle of HE (3.9.2012) surmised: ‘The term ‘MOOCs’ is meant to parallel the video-game acronym ‘MMOGs’ or massively multiplayer online games—collaborative worlds, like World of Warcraft, that have attracted millions of devoted players around the world’.

As with teachers and technology, there was also very little discussion of the **business and economic aspects** of MOOCs (n=20), with only a few headlines and definitions focusing on the potential role of MOOCs in selling higher education ('MOOCs: new money for old rope'—Times Higher Ed, 14.2.2012; 'MOOCs: vending machines of learning—Australian, 21.8.2013). Conversely, doubts concerning the profitability of MOOCs were rare—that is, 'information wants to be free, but does education?' (Washington Post, 2.11.2012); 'more to MOOCs than moolah' (Times Higher Ed, 10.1.2013). Even less concern was shown with the **content** of MOOC provision (n=18). The content of these courses was mentioned only with respect to subjects and topics of study that were seemingly incongruous in a technological setting (e.g. 'making his MOOC an "outreach for poetry"' Chronicle of HE, 29.4.2013; 'from single-digit addition to the history of Chinese architecture to flight vehicle aerodynamics' New York Times, 13.10.2013), or when MOOCs were being developed for serious provision—such as when the International Monetary Fund announced plans to establish their own MOOCs—'IMF offers public lessons in finance' (Times, 20.6.2013).

Similarly, the nature of the **learning** taking place through MOOCs was mentioned rarely (n=16)—depicted usually in terms of 'opening minds' (New York Times, 20.11.2012); 'MOOCs break down barriers to knowledge' (Australian, 12.12.2012) and even 'Ivy League online education going to give the Flynn Effect extra juice' (Washington Post, 10.5.2012). Finally, and perhaps most surprisingly, **students** were also notable by their absence from all but 15 of the headlines and descriptions. On the occasions that they did feature, this was in terms of students either being advantaged by studying in MOOCs over more traditional forms of learning ('putting students centre stage' Guardian, 9.7.2013; 'gives students what they want' Age, 5.6.2012), or conversely in need of 'rights protection' (Times Higher Ed, 31.1.2013). Otherwise, students did not appear as an integral element of what MOOCs were and what they meant.

Discussion

These news media headlines and descriptions will certainly have informed many people's understandings not only of what MOOCs are, but also their wider societal significance. From this basis, then, it would be reasonable to have drawn the following conclusions. That is, MOOCs are clearly a portentous development in the current higher education marketplace. They have emanated from elite US universities in a spirit of online expansion (and perhaps even outreach). In this sense MOOCs are reinforcing the established *status quo* in higher education—offering an alternative 'way in' to later study for 'proper' courses at 'proper', 'face to face' universities. MOOCs are courses that are taught by leading professors and, even in their most modest form, will involve thousands of students or more. The main concern that one need have with MOOCs is economic in nature, with large numbers of students engaging in university-level education for no fee or charge. In contrast, the pedagogical and technological characteristics of MOOCs are of little interest. Indeed, MOOCs are best seen as online versions of familiar university classroom pedagogies—that is, the lecture, the seminar and the tutorial. Similarly, the technological character of MOOCs is akin to familiar, established content-sharing and content-distribution applications (iTunes, YouTube, Google and so on). These familiar features reflect a sense of MOOCs either developing as part of a natural evolution of technology, or else a deliberate process of scientific innovation.

Of course, this analysis is restricted to the concerns of news media based in the US, UK and Australia. As such any conclusions need to be set against the particularities and boundaries of these respective national higher education landscapes – not least the well-established massification and marketization of university education. Indeed, the predominance of commodified 'traditional' forms of higher education in the US, UK and Australia undoubtedly have a bearing on these recent understandings of online education. As such, there is clearly room for additional comparative work that maps the discursive constriction of MOOCs in other national contexts – such as the largely publically-funded Scandinavian and central European education systems, as well as emerging higher education systems in regions such as Africa and the Middle East.

These limitations notwithstanding, there are a number of points to make about the persuasive but limited discursive constructions apparent within the news discourses examined in this paper. First, these descriptions and meanings differ considerably to the ways in which MOOCs have tended to be imagined and discussed within specialist educational technology circles. Second, these news media constructions are more straightforward, and certainly more conservative, than the increasingly contentious ways in which MOOCs are discussed on social media and in educational technology conferences, journals and other academic forums. Third, these discourses from the likes of the New York Times, Chronicle of HE, et al. reflect clearly the subsuming of MOOCs into the concerns and interests of the higher education establishment. Unlike their portrayal in many parts of the educational technology profession, MOOCs are certainly not understood as a countercultural, subversive or alternative element of higher education.

Indeed, unlike some of the prevalent discourses within online and professional domains, MOOCs do not appear to have been the subject of a pronounced deluge of hyperbole in the mainstream news media. Instead our data show a fairly consistent level of stories over the past 24 months or so—certainly not constituting a rapid over-saturation of the topic. Similarly, there has been little sign of a backlash against MOOCs in these mainstream sources. For example, while concerns over the relatively high levels of student dropout and disengagement from courses might have been mentioned elsewhere in articles, such negative issues did not rise to be key defining features or headline issues apart from a small handful of stories at the end of 2013 when mention began to be made of 'setbacks' (New York Times, 11.12.2013), 'high hopes trimmed' (New York Times, 17.12.2013) and 'MOOC disengagement' (Guardian, 13.12.2013). Only in December 2013 did an overtly critical headline appear, with the Washington Post (12.12.2013) enquiring plaintively, 'Are MOOCS already over?'.

In terms of the research questions set out at the beginning of this article, are a number of issues that therefore merit further consideration. In particular there are important questions to ask about whose interests these news media discourses and meanings about MOOCs benefit—thereby questioning the extent to which these constructions of MOOCs are situated within dominant structures of production, power and privilege. Approached in this light, then, concerns should certainly be raised over the rather anodyne depictions of the dynamics underpinning MOOCs' rise to public prominence. The notions of MOOCs either as a force of nature *or* a facet of scientific innovation both serve to obscure the socio-technical origins of these educational forms. The descriptions of MOOCs highlighted in this article are ahistorical in a number of significant and concerning ways. First, most of these stories make little or no connection between the recent rise of MOOCs and the wider struggles over higher education markets, funding and governance that have arisen in direct connection to the past thirty years of neoliberal reform of universities. In this sense, MOOCs are certainly not an unprecedented or new phenomenon—rather they are deeply implicated in the longstanding politics and economics of higher education. A second facet of this a-historicism is how these news discourses also give little credence to the past thirty years of e-learning research and practice—not least the efforts of open education and connectivist communities in originating the open courseware and 'c-MOOC' concepts during the 2000s. Indeed, only one of the 457 stories made explicit mention of the efforts of George Siemens, Stephen Downes, Dave Cormier and others ('writers of the MOOC origin story are not fans of the original' Times Higher Ed, 17.10.2013). Here too, there is a significant 'alternative' heritage of shaping influences behind the seemingly rapid rise of MOOCs that is obscured and silenced in the news media.

Also problematic is the partial visibility within news media discourses of many of the key actors and interest groups implicated in the actual growth of MOOCs. For example, these news accounts convey a narrow representation of university institutions as a small number of elite, Ivy League, 'big fish' institutions. Similarly, university teachers are portrayed predominantly as 'world leading' professors and 'rock star' high flyers. The only other high-profile actors in these stories tend to be the poster boys/girls of the major MOOC providers—the innovative inventors and 'Stanford scientists', such as Sebastian Thrun, Andrew Ng and Daphne Koller. Of course, the high level of visibility afforded to *these* elite individuals and institutions is accompanied by a corresponding obscuring of many *other* significant actors and interests. For example, as we have noted above, painfully little is said within these news accounts about students, beyond suggestions of homogenous masses of passive consumers. Little is said about the vast numbers of MOOC tutors who do not fit into the category of 'rock star'—that is, the less exalted, far less securely employed foot soldiers of higher education who are actually responsible for the bulk of MOOC teaching. Little is also said about the non-elite, non world-leading universities that are developing and running MOOCs out of 'Anytown' USA (or Canada, China, Chile and so on). Perhaps most obviously, little is said about the role of the private sector enterprises, the venture capitalists and shareholders who have invested in and around the nascent MOOC industry in the hope of riding an e-learning financial wave to big returns.

These partial portrayals all serve to obscure some of the most significant dynamics of the recent rise to prominence of MOOCs—not least power imbalances and the domination of elite interests, continued hierarchies and unequal social relations between institutions, teachers and students, and the perpetuation of long-standing inequalities of opportunity and outcome. Take, for example, the notion conveyed in mainstream news stories that MOOCs are taught by privileged professors and taken by masses of students regardless of their circumstance. This belies the reality of a situation where many MOOCs are being taught by largely undistinguished and disempowered faculty and taken/completed mainly by a minority of educated privileged students (see Emanuel, 2013). Not only are these news media discourses obscuring the emerging evidence of MOOCs benefiting students who are already academically privileged rather than democratizing educational participation, but they also serve to side-line important issues relating to the casualization, deprofessionalization and outsourcing of academic labor. Similarly obscured are issues relating to the economics of MOOCs. Where is the reporting and discussion of the role of multinational corporations such as Pearson in supporting the administration of MOOCs, or multi-million dollar investments by venture capitalists? Taken on its own terms, these news media discourses reflect little of the major implications of MOOCs with regards to the potentially radical reform of relationships between the individual and the commons, the public and the private, non-profit and for-profit interests. The over-riding sense that one gains from reading these accounts is that of MOOCs as straightforward product rather than MOOCs as complex and messy process.

Conclusions

There is much more that our research project will address in subsequent analyses—not least how these descriptions, understandings and meanings are remediated from their 'old media' origins in arenas such as the New York Times into online comments pages and then onto the blogosphere, Twitter and other social media forums. Yet while the current commentary and debate about MOOCs undeniably is taking place on a diverse poly-medial basis, it would be unwise to dismiss the discursive construction of MOOCs in the established news media sources covered in this article as somehow peripheral to 'real' meaning-making in the digital age. On the contrary, these old media continue to be sites where the vast majority of the general public (and a good proportion of education professionals) are being exposed to the notion of 'MOOCs'. These also are the media sources that continue to exert a disproportionate influence on policymakers and decision-makers, both in government and within higher education institutions. As such, these news media should be seen as having a large bearing on the continued progression of MOOCs from niche educational technology fad to mainstream educational form.

Seen in this light, then, there is clearly a need for more informed and nuanced descriptions and meanings to be added to these debates within news media around the world. While it might appear a minor matter, contesting the language, definitions and implicit assumptions currently being used to describe MOOCs within popular discourse could be seen as an important task for those in the educational technology and e-learning communities to take up. As the data in this article have demonstrated, language and discourse are integral elements of the politics of contemporary education—maintaining the parameters of what is, and what is not, seen as preferable and possible. Challenging—and offering alternatives to—something as apparently trivial as the ways in which MOOCs are being talked about in mainstream news media is therefore an important element of influencing the future conditions of digital higher education. Supporters and opponents of MOOCs in their various guises are well advised to take note, and to take action.

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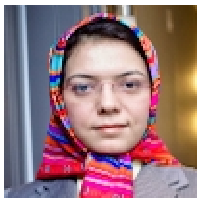
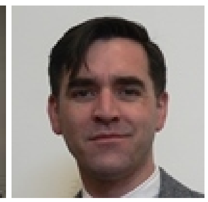
[i] The choice of these three countries was based on a number of practical criteria. In order to give our analysis depth as well as bredth, we wanted to focus on complete sets of articles from a limited number of authoritative news media sources. Given the linguistic and educational backgrounds of the research team, we concentrated on three Anglohone countries in which we had detailed experience of the higher education systems.

THE INTERNATIONAL REVIEW OF RESEARCH IN OPEN AND DISTANCE LEARNING

MOOC Integration into Secondary School Courses





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Abstract

We investigated how high school students taking a university preparatory economics course would engage with the learning and assessment components of a Behavioural Economics MOOC that was integrated into their school-based course. Students were divided into two groups, MOOC-only, with no teacher support, and blended-mode, with weekly tutorials. MOOC only students scored slightly lower on a teacher designed knowledge test but scored slightly higher in a MOOC test. Although the MOOC-only students watched more unique videos, the blended-mode students stayed more on-track with the MOOC. The blended-mode students showed more persistence in retaking quizzes, yet they scored lower than the MOOC-only students.

Introduction

Massive online open courses (MOOCs) have been used in various ways often in the form of a flipped classroom, to complement traditional classroom teaching through integration of a whole course or specific parts of a course both in K-12 and in higher education. High school students, for example, could use MOOCs for university preparation in the absence of available face to face or online courses or in addition to them (Vihavainen, Luukkainen, & Kurhila, 2013). Furthermore, contents of a live or an archived MOOC could be integrated into an existing course in a hybrid format (Bruff, Fisher, McEwen, & Smith, 2013).

In this research we investigated how high school students taking a university preparatory economics course would engage with learning and assessment components of a Behavioural Economics MOOC that was integrated into their school-based course. Of specific importance to this research was probing any potential difference in students' use of various components of the integrated MOOC depending on receiving supplementary instructional support or studying on their own. For this purpose, three weeks of the "Behavioural Economics in Action" (BE101x) MOOC were chosen for integration into the school-based course "Analyzing Current Economic Issues" (ACEI). Twenty nine students from a Canadian independent university preparatory school who had enrolled in ACEI were randomly assigned to two groups for the BE101x integration period with one group studying on their own and the other receiving weekly tutorial sessions from their classroom teacher. Here, we report on how students in the two groups engaged with the learning and assessment components of BE101x and persisted throughout the three weeks of integration. Also, we compare students' outcomes based on pre-post BE101x-integration content knowledge surveys and BE101x assessments.

Review of Related Literature

Research on online university preparatory courses, MOOC-like university preparatory courses, and MOOC integration in credit courses informed our study.

Online University Preparatory Courses

Online advanced placement (AP) courses could increase students' access when face to face options are not viable due to restricted budgets or geographical location. In Newfoundland and Labrador, for example, the percentage of students in rural schools who enrolled in advanced-level courses through the Centre for Distance Learning and Innovation was higher than the provincial average (Barbour, & Mulcahy, 2013). Similarly, students in Florida who enrolled in online AP courses available to all students, regardless of income level and district budget, scored higher than the state average in their AP exams (Johnston, & Barbour, 2013). Yet students who participated in a follow up interview reported a preference for face to face classes where they could readily communicate with a teacher and improve their performance based on teacher feedback. Teacher presence in online secondary school courses positively affected student outcomes in introductory mathematics courses (Liu & Cavanaugh, 2012). For more advanced courses, on the other hand, the amount of teacher feedback was negatively related to course outcomes which may indicate that to be successful in more advanced online courses, high school students need to be self-directed and less reliant on teacher feedback. Time spent in the online course environment was another factor that would have a positive effect on students' assessment outcome.

MOOCs for Curriculum Enrichment and Reach-Ahead

Some MOOCs have imposed minimal prerequisites for registration, and high school students have already established themselves as a demographic group in MOOCs of various difficulty level (Breslow et al., 2013). 2.39% of survey respondents of an electronics MOOC, with suggested academic prerequisite of having advanced knowledge of electricity and magnetism, reported their highest education level to be below high school diploma (DeBoer, Stump, Seaton, & Breslow, 2013). In terms of course achievement, however, total points gained by those students with junior high school education level were comparable with students holding a bachelors degree.

Aside from MOOCs offered to the general public, specialized MOOCs have been developed for middle and high school students, either as university preparatory courses or as high school level courses. To address the paucity of pedagogically sound high school level computer science curricula, a mini course titled "Foundations for Advancing Computational Thinking" (FACT) was developed on the Stanford OpenEdX platform and piloted in a public middle school (Grover, Pear, & Cooper 2014). The FACT mini course has demonstrated promising results regarding students' learning and it is being offered as a MOOC for either self-study or for teachers to use in their computer science classrooms. A similar project, MyCS, geared towards middle school students, was also considered for further development as a teacher-mediated computer science MOOC (Schofield, Erlinger, & Dodds, 2014).

To reinforce students' knowledge of science and mathematics and to facilitate their entrance to universities, an Italian school board implemented high school specific online open courses by recording classroom lectures and making them available online (Cannesa & Pisani, 2013). Test results showed that students who watched online lecture videos in addition to their face to face classroom scored higher than those who only relied on face to face classroom learning. Although not a typical MOOC in terms of design, this project supports the notion that self-paced open access material, geared towards high school students may increase students' depth of learning and academic success. In another study, a university preparatory mathematics MOOC was developed to increase mathematical proficiency of incoming students (Daza, Makriyannis, & Rovira Riera, 2013). First year university students were encouraged to participate in the MOOC voluntarily while the MOOC was also open to the public. Initial findings, showed students level of satisfaction with the contents of the MOOC, although the impact of MOOC learning on students' success was not measured due to the scope of the study.

While several projects such as the University of Wisconsin's College Readiness Math MOOC and the MIT physics MOOCs offer preparatory courses to secondary school students, research on the impact and implications of such initiatives is still in its infancy.

MOOC Integration

With respect to integrating existing MOOCs into regular classroom instruction, flipped classrooms could offer one model. In flipped classrooms, the online component, for example the MOOC, allows students to prepare for in-class discussion by reviewing relevant material beforehand and at their own pace. In other models of integration, even MOOC assessments could count towards students' evaluation of the on-campus course. The instructor of a machine learning graduate course, for example, integrated an archived MOOC into his face to face course where students were required to take MOOC quizzes and write MOOC assignments, submitted to their instructor, in addition to covering learning components of the MOOC. Students responded positively to the experience and noted that the face to face classes would help them keep track of the self-paced MOOC component (Bruff et al., 2013).

Research Questions

In this study, we examined potential impacts of the presence or absence of teacher support on secondary school students' behavior and outcome during a MOOC-integration initiative. Three research questions guided our study:

- How do students in MOOC-only and blended-mode groups differ in their learning outcomes?
- How do students in MOOC-only and blended-mode groups differ in the level of engagement with the learning and assessment components of the integrated MOOC?
- How do students in MOOC-only and blended-mode groups differ in their persistence to complete the activities of the integrated MOOC?

Methods

A case study encapsulates our research design in examining the impact of different levels of instructional support on students' engagement with learning and assessment components of BE101x and their outcome as evident in MOOC quizzes and knowledge-based tests. To this end, BE101x integration in the ACEI course could be an instrumental case (Stake, 1995) that allows us to gain insight into the issue of using MOOCs in the context of a secondary school course.

Research Context

This study was conducted in the context of a university preparatory economics course at a competitive independent Canadian school from October 14 2013 to November 21 2013. The two participating class sections were taught by an experienced teacher, also a co-investigator of the study. The age range of students enrolled in this course was between 15 to 17 years. Twenty nine students agreed to participate in the study out of a total of 32 students. Participation in this study was voluntary and had no impact on students' formal evaluation and course outcomes.

BE101x, a six week MOOC on edX, was first offered in October 2013. Consequently, this study coincided with the live offering of this MOOC. Below we discuss curriculum design considerations, research timeline, participant recruitment, and grouping procedures.

Curriculum Design

Integration of BE101x in ACEI was temporally bound between October 14, 2013 and November 18, 2013, weeks 1 to 5 of the BE101x MOOC. Before the study started, the teacher compared the contents and objectives of BE101x and ACEI to find areas of overlap where BE101x could be most effectively integrated.

Weeks 1, 2, and 5 of BE101x MOOCs were selected for integration. ACEI's start time coincided with the first week of BE101x. Timeline, themes, learning components and assessment components of weeks 1, 2, and 5 of BE101x were as follows. Note that only those learning components that preceded a quiz or a debate were accounted for.

- Week 1 (October 14 to 20): Introduction to Behavioral Economics.
  - 5 lecture videos, one article accompanied by slides, and 6 quizzes
  - Debate video and week 1 debate
- Week 2 (October 21 to 27): Mental accounting
  - 7 lecture videos and 7 quizzes
  - Debate video and week 2 debate
- Week 5 (November 11 to 17): Nudging
  - 8 lecture videos, 2 articles, 10 quizzes
  - Debate video and week 2 debate

Prior to the start of the study, students were randomly divided into two groups for research purposes: a MOOC-only group with 14 students and a blended-mode group with 15 students.

In the three weeks outlined above, regular classes were not held. Instead, students in the MOOC-only group would study BE101x independently with no support from their teacher. On the other hand the blended-mode group students met their teacher once a week in an hour-long tutorial session. Materials from these sessions were given to MOOC-only students after week 5.

Tutorials were structured to include three common sections: Questions and answers, Experiment/Business problem, and an Individual exercise. The purpose of these tutorial sessions was to elaborate on BE101x themes and engage students in applying what they had learned during that week. The dates of these tutorials were: week 1, October 21, 2013; week 2 , October 28, 2013; and week 5 , November 18, 2013.

Students would attend regular classes in weeks 3 and 4, between October 29 and November 10, 2013. Upon the culmination of week 5 of BE101x, regular classes were resumed for the rest of the school term.

Students received an email prior to the start of their course that explained the study and its goal. This email was followed by another orientation email sent from the teacher on the first day of BE101x asking students to sign up for the MOOC on edX and also recommending that they refrain from starting the course until October 16th where a face to face orientation class meeting would be held.

Time and date for knowledge-based pre and post tests were also shared with the students. On October 16, 2013 the teacher met all of the students where the students received further explanation about BE101x and the study and took a knowledge-base pre-test. The teacher explained that the students would not be evaluated on their participation in BE101x and that participation and the extent of engagement were absolutely the responsibility and choice of the students.

Data Sources

To maintain student anonymity, we refrained from using any data that could lead to revealing their identity including their contributions to BE101x discussion forums and weekly debates. We collected data from the following sources.

- Clickstream data of BE101x between October 14, 2013 and November 21, 2013. We selected specific events in the clickstream that could reveal differences in use of and engagement with the integrated BE101x resources between the MOOC-only and the blended-model groups. For videos, we specifically considered "play_video" and "pause_video" events to determine if a video was watched. "Load_video" event were disregarded as it is generated when a page containing a video is loaded and this does not necessarily mean that the video was played. In the duration of BE101x integration students couldwatch a maximum of 6 debate and debrief videos and 20 lecture videos.

- Content knowledge pre-post questionnaire. The teacher designed a 10-item true/false questionnaire that students wrote in class in the week of October 14, 2013 and again in the week of November 18, 2013 after the MOOC integration culminated.

- BE101x quizzes in weeks 1, 2, and 5 and BE101x test in week 3. The test in week 3 covered material from weeks 1 and 2. Data related to quizzes taken, number of attempts, and final score was extracted from the database for students in both groups. Another test was written in week 6 of the course but students' performance in this test could not be extracted from the raw data.

Data Analysis

Three dimensions of student engagement, student persistence, and student outcomes during the duration of their MOOC participation were of importance to this research.

Student engagement related to students' use of and access to BE101x learning components, specifically lecture videos that preceded each quiz, debate videos, and debate debrief videos. These learning components were located within the clickstream data by their unique identifiers. Four quizzes were preceded directly by either articles or slides. We could not track them in the clickstream data and thus did not include them in our analyses. For student engagement dimension, we compared the two groups on unique videos accessed, total number of videos accessed, and videos accessed on-track with BE101x pace.

Student persistence referred to the number of quizzes they took in weeks 1, 2, and 5 of the integration and if quizzes were retaken until a perfect score was achieved. The last dimension, student outcome, attended to differences between MOOC-only and blended-mode groups on their performance in BE101X test, overall quiz score, and in content knowledge pre-post tests. We would like to note that technical problems in extracting clickstream data largely affected the depth and scope of our analysis.

Findings

Students' Learning Gains and Outcome

Students' scores in content knowledge pretest, written at the start of BE101x integration, and posttest, written after the integration was over, showed an increase in their knowledge of Behavioural Economics. As illustrated in Figure 1, MOOC-only students scored lower in the pretest (M= 4.91; SD= 1.08) compared to blended-mode students (M= 6.06; SD= 1.86). In the posttest, despite performing better than the pretest (M= 7.75; SD= 1.42), MOOC-only students still gained lower scores than the blended-mode students (M= 8.53; SD= 1.68). A two sample t-test did not show a significant difference between the two groups on their posttest scores; $t(25)=1.28$, $p=0.1$.

A BE101x test written in week 3 provided another measure for students' outcome. Unlike the content knowledge posttest results, students in the MOOC-only group scored higher (M= 12.73, SD=1.38) than the blended-mode group students (M=11.53, SD=3.06). A two sample t-test did not reveal a significant difference between the two groups, $t(23)=0.94$; $p=0.17$.

We investigated if the observed overall difference between the MOOC-only and the blended-mode groups in terms of their pretest and posttest scores also reflected in their level of persistence and engagement with learning and the assessment components of the integrated MOOC.

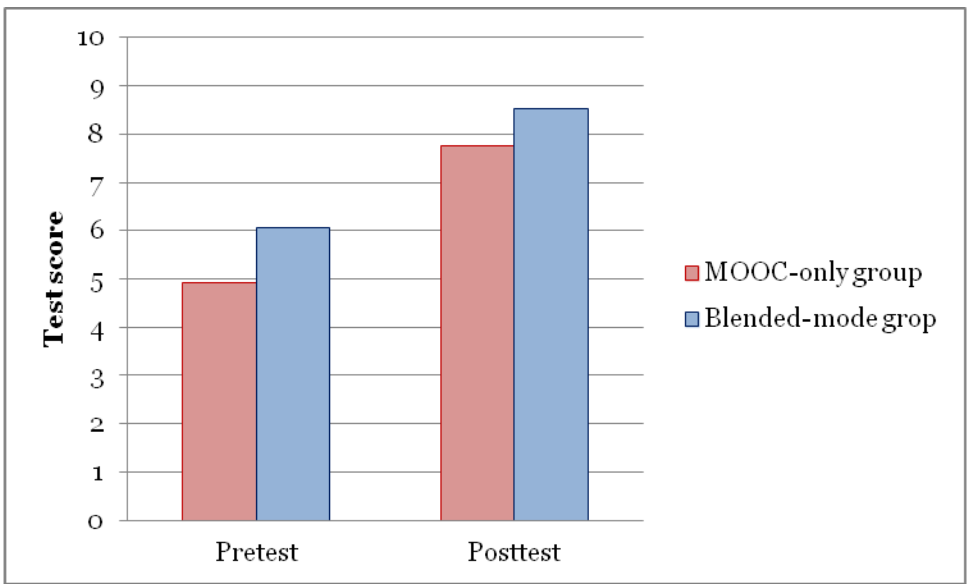

Figure 1. Students' performance in pretest and posttest.

Overall Activity During MOOC Integration

During the running of the course, students were free to login to BE101X whenever they desired. However, only student access to BE101X between October 14, 2013 and November 21, three days after the third tutorial session, was specifically relevant to our research. We started by, first, examining the number of students in both groups and in total who accessed the integrated BE101X at least once in each day between October 14, 2013 and November 21. Although weeks 3 and 4 of BE101X were not integrated into

ACEI, we included these two weeks in our analysis as we assumed that students may have reviewed week 1 and week 2 material or have caught up with activities that they had missed.

The number of students who logged into the integrated BE101x in weeks 1, 2 and 5, in addition to weeks 3 and 4 in between, is shown in Figure 2. We corroborated high and low levels of activity with important dates during the integration period. Note that any activity before October 16 is negligible as students were not yet divided into groups.

The highest level of activity occurred on the two days when BE101X week1&2 and week5 tests were administered, October 31, 2013 and November 21, 2013 respectively. The day of the first tutorial showed another peak of activity with 7 MOOC-only and 9 blended-mode students online. A high activity level is observed on November 18 for the blended-mode group, which can be attributed to the third tutorial session. As expected, the level of activity was low for both groups after the October 31 test and remained relatively low throughout week 4. Both groups were comparable in the level of activity until November 16, 2013 when a peak of activity is evident for the blended-mode students that was sustained until November 18 and then dropped quickly in the next two days. In that three-day period, students in the MOOC-only group maintained a lower level of activity. However, their activity level steadily increased and eventually equated with the blended-mode students in the two days leading to test 2 on November 21, 2013.

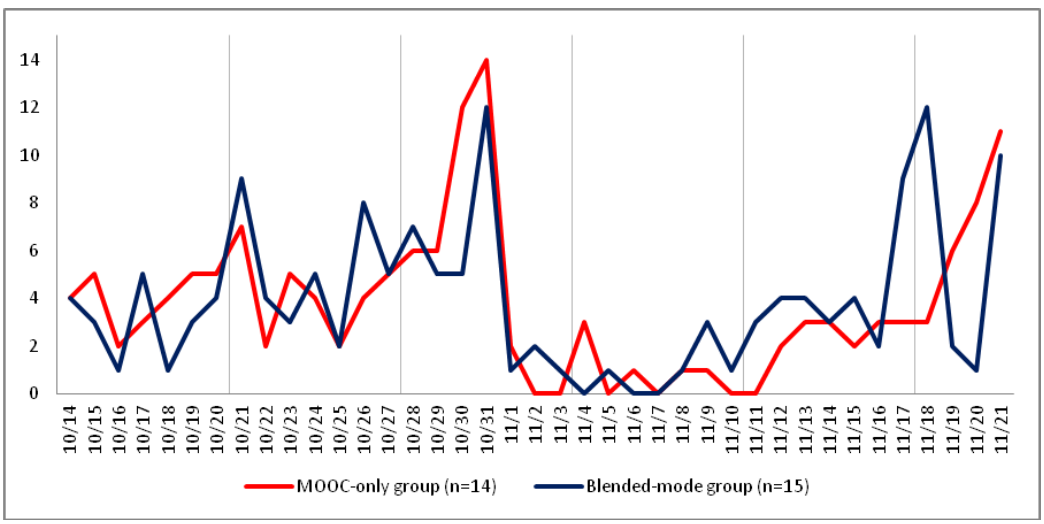

Figure 2. General trend in students' activity in the integrated BE101X and in the two weeks in between based on the number unique daily online users.

Use of Resources: Unique Number of Videos Accessed

We examined students' access in both groups to the lecture videos that would precede a quiz in weeks 1, 2, and 5. First, we calculated the number of unique lecture videos, debate videos, and debate debrief videos students had accessed in the duration of

BE101x integration, including weeks 3 and 4. Table 1 summarizes descriptive statistics relevant to unique videos that students in both groups watched.

Table 1

Students' Access to Lecture Videos and Debate/Debrief Videos

Group	Lecture videos		Debate/Debrief videos	
MOOC-only (n=14)	M=18.00	SD=4.33	M=2	SD=1.35
Blended model (n=15)	M=16.46	SD=5.42	M=1.8	SD=1.65

MOOC-only students on average watched, that is, played, more unique videos than students in blended-mode group. Overall engagement level with lecture videos based on the average number of lecture videos watched was close to a maximum of 20 videos in both groups.

To better understand any noticeable differences in how students in the two groups accessed unique lecture videos of the integrated MOOC, we graphed the percentage of students in each group who watched lecture videos of week 1, week 2, and week 5 at least once any time during the integration and in the two weeks in between. As depicted in Figure 3, 80% of all lecture videos, were watched by more students from the MOOC-only group. For the rest of the lecture videos, the difference between the number of blended group students and MOOC-only group students who watched those videos was a maximum of two students. Throughout the three weeks and between the two groups, the percentage of students watching lecture videos fell slightly with only one of 7 videos being watched by more than 90% of the students. This number was 6 out of 6 for the week 1 video and 3 out of 7 for the week 2 lecture videos. Still, the overall lowest percentage of students watching a lecture video, which is a week 5 lecture video, was nearly 67% by students in the blended-mode group.

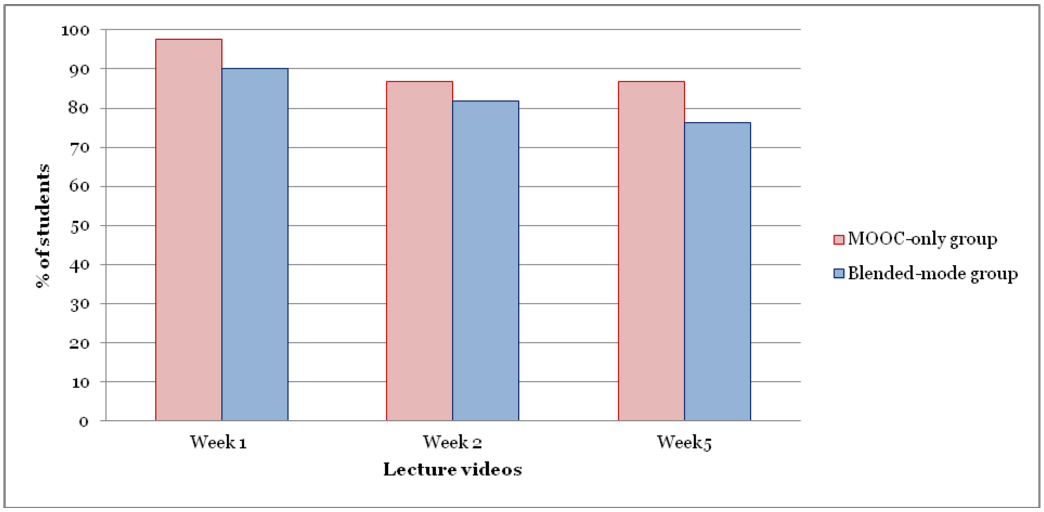

Figure 3. Percentage of students in each group who watched lecture videos.

Remaining On-Track or Lagging Behind

Students in both groups watched most of the lecture videos belonging to three weeks of BE101x integration. However, we questioned if students would have followed the course week by week or would have lagged behind and compensated later. Thus, for both groups, we examined if students watched lecture videos of a given week at least once during that week.

Table 2 summarizes the average percentage of lecture videos in weeks 1, 2, and 5 that were watched within those specific weeks. As Table 2 shows, on average, students in blended-mode group following the BE101x course pace watched lecture video more than their peers in the MOOC-only group. Week 2 engaged the highest number of students in both groups in watching lecture videos as MOOC-only students and blended-mode group students watched 43.88% and 63.81% of lecture videos between November 21, 2013 and November 27, 2013.

Table 2

Percentage of Students who Watched Lecture Videos On-Track

	Week 1 videos	Week 2 videos	Week 5 videos
MOOC-only group (n=14)	36.9%	43.88%	33.67%
Blended model group (n=15)	46.67%	63.81%	51.43%

We, then, considered if there were students in both groups who consistently remained on-track during the three weeks of integration or consistently lagged behind. In weeks 1, 2, and 5, four MOOC-only students, 28.57%, completely stayed on track whereas six others, 48.85%, completely lagged behind and watched none of the lecture videos belonging to those weeks. These numbers for the blended-mode group were three students, 20%, and four, 26.66% respectively.

Figure 4 and figure 5 show the difference between the two groups regarding following the pace of the integrated MOOC by watching lecture videos in Weeks 1, 2, and 5 on-track, in more detail. More students from blended-mode group followed the pace of the course for more than 80% of the lecture videos. Consequently, although a higher percentage of MOOC-only students watched all videos following the pace of the course, blended-mode students as a group remained on-track more consistently.

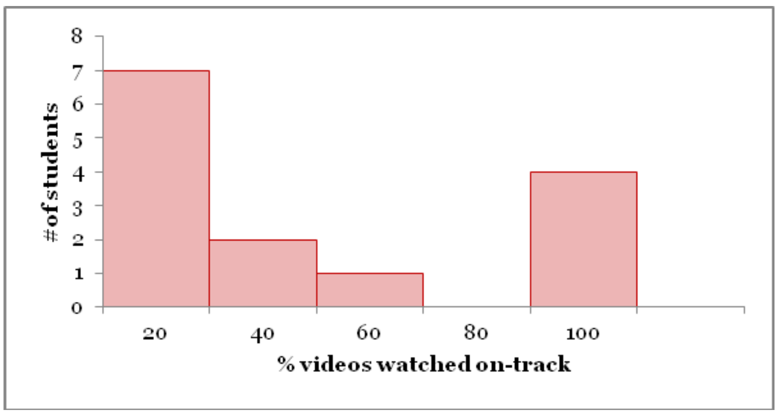

Figure 4. MOOC-only students' pace of watching lecture videos.

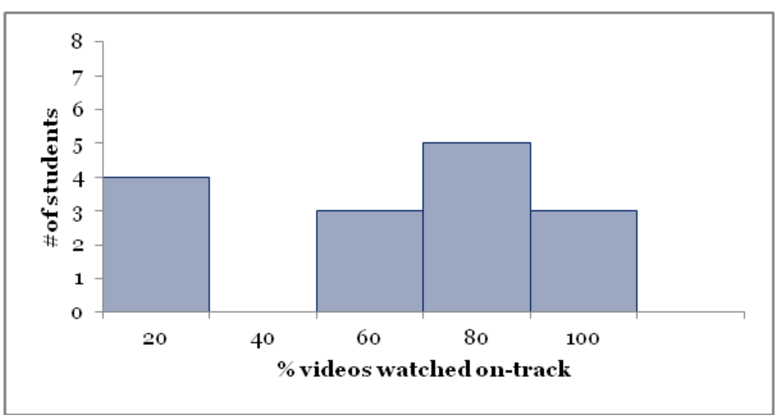

Figure 5. Blended-mode students' pace of watching lecture videos.

Engagement With and Persistence In Quizzes

Students could take a total of 29 quizzes with a maximum total quiz points of 29. A quiz would only be graded if students chose to submit their answer. As a result, a zero quiz point would either mean that the student submitted an incorrect answer, or else, the student did not take the quiz at all. To examine students' performance in quizzes in the MOOC-only and blended-mode groups we considered total points received in all of the 29 quizzes regardless of whether a quiz was actually submitted for grading. We factored such differences into our analyses of how students attempted to retake quizzes to achieve maximum points possible.

Students in the MOOC-only group received slightly more points in quizzes (M= 24.95; SD=5.98) than students in blended-mode group (M=23.74; SD=7.43). Regarding the number of quizzes taken, out of 29 quizzes, MOOC-only group submitted more quizzes for grading (M=26.42; SD=6.08) compared to blended-mode group students (M= 24.53; SD=7.69).

Finally, we investigated students' persistence while taking quizzes in terms of achieving maximum quiz points possible for the number of quizzes taken. Blended-mode group students outperformed MOOC-only students in persistence as 40% of the former versus 21.42% of the latter correctly answered the quizzes that they submitted for grading.

Discussion

Of specific importance to this research was probing any potential differences in students' use of learning and assessment components of the integrated MOOC depending on receiving supplementary instructional support or studying on their own. Students' scores in the pretest, written before starting the integrated BE101x, and posttest, written after the integrated BE101x was over, showed an increase in their knowledge of behavioural economics. Thus, the integration had no adverse effect on students' learning.

With the opportunity to expand on BE101x content in the three tutorial sessions, we would expect blended-mode students to watch more video lectures and be more engaged with these learning components. Surprisingly, MOOC-only students on average watched more unique videos than students in blended mode group. Regarding students' performance in MOOC quizzes, MOOC-only students were at no disadvantage as they received more quiz points compared to blended-mode students. However, we noticed that students from the blended-mode group were more likely to retake quizzes to achieve complete quiz points.

MOOC quizzes, considered as data sources for this study, may only reveal students' ability to recall information. The specific MOOC discussed in this study also contained knowledge transfer and application assignments and weekly debates that were not included as data sources. We also inferred from clickstream data that students participating in this study did not participate in the MOOC's discussion forum. However, with the evidence that students would access MOOC resources and take quizzes with no direct contact with their classroom teacher, we posit that MOOCs could provide another means for reaching ahead and preparing for university for students who rely on online advance course for reasons such as geographical location (Barbour & Mulcahy, 2013).

In this study, we questioned if students would have followed the course week by week or would have lagged behind and compensated for it before the tests in week 3 and week 6 to cover lecture videos. Fewer students in the blended-mode group lagged behind, which could be attributed to the weekly face to face tutorials. Previous research confirms this finding (Bruff et al., 2013) that instructional presence may positively affect students following the expected pace of integrated content.

Although a higher percentage of MOOC-only students watched all videos following the pace of the course, blended-mode students as a group remained on-track more consistently. Knowing that they would discuss lecture videos of a given week during the tutorial session, these students would have preferred to attend the class prepared rather than postponing watching lecture videos to a few days before test 1 in week 3 and test 2 in week 6.

Empirical literature to investigate potential learning benefits of developing MOOCs or MOOC-like initiatives for specific age or grade level group is still in its infancy. Existing studies either report on preliminary findings in the form of overall satisfaction (Daza et al., 2013) or improved test results (Cannesa & Pisani, 2013) or propose the development of a MOOC based on pilot projects (Grover et al., 2014; Schofield et al., 2014). We contributed to this growing line of research, by comparing how high school students engage with a MOOC integrated into their school-based course, in a self-directed manner or with teacher support.

Conclusion

The results of our study are promising regarding integrating MOOCs in school-based courses in a self-study manner. Students engaged with learning and assessment components of an integrated MOOC in a self-study manner. It is important to note however, that participants of this study were high achieving and intrinsically motivated students which may have affected their level of engagement. Integrating MOOCs into school-based courses entails curriculum design challenges as classroom teachers need to find relevant content that enriches their existing curriculum. One implication would be for teachers to carefully examine the added cognitive value of MOOC integration. Another challenge is the persistence of an integrated MOOC over time. In case an integrated MOOC is removed from its provider platform, the teacher may have to look for a replacement or abandon the integration. MOOCs specifically developed for school courses may alleviate such problems.

Understanding students' experience through interviews and detailed reflection notes would shed more light on their perception of the usefulness of the integration and the challenges they may have faced. This study only included quantitative measures but our next round of research will also consider in-depth qualitative data related to the MOOC integration design process, student interviews and reflection, and a knowledge integration project as data sources so that we are able to compare the intended and the implemented MOOC integration effort in more depth.

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