Fostering Discussion across Communication Media in Massive Open Online Courses

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Abstract: This paper presents data from one cycle of a design based research process in which we grapple with challenges in engaging students in more intensive discussion based interactions in Massive Open Online Courses (MOOCs). We compare across three communication media provided to students in that context in terms of relative popularity and overlap in student sub-populations. We also compare the communication between these contexts in terms of their content focus, concentration of reasoning articulation, and the interaction between the two. This comparison allows investigating the specific contribution of synchronous collaboration in a MOOC, which is relatively novel. The analysis suggests that there is value in providing a diverse set of discussion contexts in that they may lend themselves to differently natured interactions, but that it creates a need for greater efforts towards effective bridging between media and channeling of students to pockets of interaction that are potentially of personal benefit.

Keywords: discussion affordances, massive open online courses, reasoning

Introduction

As the field of online education increases its focus on delivery of effective instruction at massive scale as in Massive Open Online Courses (MOOCs), we become more painfully aware of teaching resources as a limited commodity. Analyses of attrition and learning in MOOCs both point to the importance of social engagement for motivational support and overcoming difficulties with material and course procedures (Breslow et al., 2013). Furthermore, we learn from the field of Computer Supported Collaborative Learning (CSCL) that with proper support, students can learn substantially from their interactions with other students (Fischer et al., 2013). However, the reality of current content-focused xMOOCs, such as the typical MOOCs offered through Coursera, edX, and Udacity, is that opportunities for exchange of ideas, help and support are limited to threaded discussion forums, which are often not well integrated with instructional activities and as a result lack many of the qualities identified as reflecting instructionally beneficial interactions from prior work in the field of CSCL (Rosé et al., 2014). In contrast, constructivist MOOCs, or cMOOCs, typically provide an eclectic variety of affordances for social interaction including blogs, Twitter communication, email, Facebook study groups and others, with the idea that students should have the freedom to find a context for learning socially within this variety that they feel comfortable with, which may be effective for engendering a wider variety of discourses contextualized within the learning and therefore meeting different instructional needs (Siemens, 2005; Smith & Eng, 2013). One downside of this approach, however, is that many students find the variety disorienting and anxiety-inducing, especially those who lack appropriate self-regulated learning skills.

This paper presents data from one cycle of a design based research process in which we grapple with these trade-offs as we seek effective practices for incorporating theory-motivated discussion based learning opportunities in MOOCs. Specifically, we aim to import from the field of CSCL insights into the specific affordances for instructionally beneficial conversational interaction offered by alternative online discussion contexts as well as insights into what might be productive strategies for moving among them so that appropriate, integrated support and guidance for students could be designed and offered. In the first cycle within this iterative process, which we report on in this paper, we have developed two interventions to address specific limitations we have seen in the current generation of xMOOCs, and then deployed them in a recent edX MOOC. In the remainder of the paper we describe the prior work that motivated the design of these interventions. We then present our deployment effort and the interpretation of the data that has been collected during the first two weeks of this edX MOOC that provides the context for our study. Finally, we conclude with plans for next steps in the iterative design based research process.

Foundational work

The central means of communication provided by many courses is still the traditional web forum. Nevertheless, Web 2.0 technologies provide diverse opportunities for discussion in MOOCs, some of which have been utilized in that context. However, so far there is no coherent vision for seamless, effective integration of these technologies with MOOC based instruction. Instead, social communication in MOOCs, as in the web in general, is both eclectic and highly fragmented. For example, it is almost a given that for typical MOOCs, several groups in social networks such as Facebook or Google+ are created and sometimes actively maintained by the student population, but much more frequently quickly abandoned. Twitter is another social media outlet that is sometimes used in MOOCs, more often in cMOOCs than xMOOCs, which is mainly used as a broadcast medium but also exhibits instances of short public discussions. Discussion may also take place in connection with blog posts. This eclectic organization leaves students not having a clear picture of where to go to engage in discussion that interests them (Smith & Eng, 2013).

Most agree that social interaction in general and discussion in particular is not a major portion of the experience the majority of MOOC students have. Nevertheless, the inner workings of student experience in that context has been investigated in early work on MOOCs. Recent work studying social interaction in MOOCs has focused on identifying factors associated with attrition rather than learning (Wen et al., 2014a; Wen et al., 2014b; Yang et al., 2014). The motivation for this work is that scarce human resources could be channeled to where they are most needed, or augmented with automated forms of just-in-time support, that might enable students to persist in the course through times of elevated vulnerability. These hypotheses about what factors would ultimately flag students at risk have been validated by utilizing a statistical analysis technique referred to as survival analysis, which has been used to gauge the impact of time variant factors on dropout in other types of online communities (Wang, Kraut, & Levine, 2012). Factors that have been successfully modeled through discourse analytics, and which have been validated as significant predictors of dropout using survival modeling, include motivation and cognitive engagement (Wen et al., 2014a), student attitudes towards course affordances and tools (Wen et al., 2014b), satisfaction with help received, and relationship formation and loss (Yang et al., 2014). Of all of the factors explored so far, the most dramatic impact on attrition was related to relationship formation and relationship loss in the MOOC discussion forums, even though the students who participate in those forums are among the most highly committed to the course to begin with.

In these results we find support for the importance of community, and evidence of the potential positive impact of work towards integration in the community, and engagement in joint meaning making towards deeper engagement with the course materials. If students drop out of a course early, no matter how valuable the instructional materials are, students will not have the opportunity to benefit from them. Beyond issues of attrition, the literature on discourse analytics in the context of MOOCs also views conversational interactions from the standpoint of what is valuable for learning. Across many different frameworks for characterizing discourse patterns associated with successful collaborative learning, the idea of eliciting articulation of reasoning and idea co-construction is a frequent central element (Chan, 2013; Chin & Clark, 2013; van Alst, 2009). Thus, in our work it is a specific goal to provide affordances for engaging in this behavior through scaffolded synchronous collaboration, which is novel in a MOOC context. In contrast to other studies comparing features of communication across media (Meyrowitz, 1998; Watson-Manheim & Balanger, 2007), the goal of our specific investigation is to understand how MOOC students in a platform that includes choices in where to engage in discussion, choose to engage differently in learning relevant practices such as articulation of reasoning and help exchange across communication media.

MOOC design

Building on the understanding gained through analysis of conversational interactions in a wide variety of instructional settings, interventions have been developed and successfully deployed in both classroom and online settings that support effective collaboration and learning in those settings. In this section we describe two interventions designed to provide opportunities for discussion based learning. While one of the interventions focuses on help exchange, the other focuses on collaborative reflection. Both interventions were deployed in a nine week long MOOC on Data, Analytics and Learning (DALMOOC) that was offered on the edX platform between October and December 2014 with a total of 20,991 registered students. Our analyses are focused on the first two weeks of the course since that was the time of most intensive usage of the conversational interventions.

The Quick Helper

The first intervention, called the Quick Helper, is designed to support help seeking as well as increase the probability that help requests will be met with a satisfactory response. While virtually all MOOCs offer threaded discussion affordances where students can post help requests, some students are reticent to ask for help, and

even when students do post help requests, many of these requests go unanswered. Our help seeking intervention connects students, whose questions may go unresolved, with student peers who may be able to answer their questions. The Quick Helper is continuously available to students by means of a button. When they click, they are guided to formulate a help request. The help request is posted to the DALMOOC discussion board, and the text and metadata are forwarded to our Quick Helper system. Using this help request, a social recommendation algorithm selects three potential help providers from the pool of student peers. The student is then given the option to invite one or more of these potential helpers to their thread as shown in Figure 1. Once selected, an email with a link to the help request thread is then automatically sent to the selected helpers inviting them to participate in the thread. In the first two weeks of DALMOOC, 77 unique students elected to use our Quick Helper system approximately 127 times. Further discussion of our initial interventions applied to Quick Helper and its results are out of the scope of this paper.
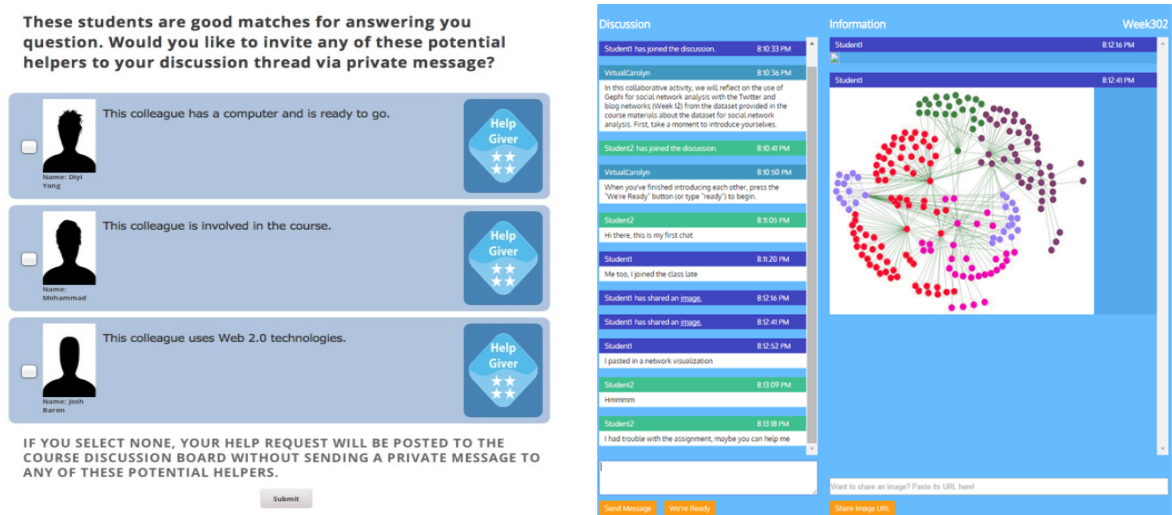

Figure 1. A screenshot of the helper selection in Quick Helper (left) and the Bazaar Collaborative Reflection chat (right).

Bazaar Collaborative Reflection

A second intervention, referred to as Bazaar Collaborative Reflection, makes synchronous collaboration opportunities available to students in a MOOC context. Research in Computer-Supported Collaborative Learning has demonstrated that conversational computer agents can serve as effective automated facilitators of synchronous collaborative learning (Dyke et al., 2013). However, typical MOOC providers do not offer students opportunities for synchronous collaboration, and therefore have not so far benefitted from this technology. Students click on our Lobby program and are matched with one other student that is also logged in to it. Once matched, they are provided with a link to a chat room where they can work with their partner students on a synchronous collaboration activity, supported by a conversational computer agent. This work builds on earlier findings from a series of studies where a Computer Facilitator has improved learning during collaboration (Dyke et al., 2013; Adamson et al., 2014).

In order to gain a deeper understanding of the problems that may arise from synchronous collaborative activities in MOOCs, we integrated a collaborative chat environment with interactive agent support. In order to facilitate the formation of ad-hoc study groups for the chat activity, we make use of a simple setup referred to as a Lobby. Students enter the Lobby with a simple, clearly labeled button integrated with the edX platform. In order to increase the likelihood of a critical mass of students being assigned to pairs, we suggested a couple of two hour time slots during each week of DALMOOC when students might engage in the collaborative activities. These timeslots were advertised in weekly email newsletters. However, the chat button was live at all times so that students were free to attempt the activity at their convenience.

Upon entering the lobby, students are asked to enter the name that will be displayed in the chat. When successfully matched with another learner, the student and their partner are then presented with a link to a chat room created for them. If another student does not enter the Lobby within a couple minutes, they are requested to return later. A visualization is presented to the student that illustrates the frequency of student clicks on the button at different times of the day on the various days of the week so that they are able to determine the best time to return. Students enter the synchronous chat room via the link, and interact with each other as well as a conversational agent who appears as a regular user in the chat, as shown in Figure 1. This chat setup has been

used in earlier classroom research (Adamson et al., 2014). In our initial investigation in DALMOOC, we make use of statically scripted agents who guide the students through course-related discussion questions but future investigations may include agents that dynamically react to the students as in our earlier work (Dyke et al., 2013; Adamson et al., 2014).

Method

The goal of our analysis is to compare across three communication media affordances for help exchange and collaborative reflection. Since the first week of the course may be anomalous due to students getting oriented to the organization and material, we sampled from two different weeks. We avoided sampling from the same students in the two weeks as much as possible in order to minimize any statistical dependencies between weeks.

Data

Table 1: Descriptive statistics over sampled communication data for analysis

	Unique Students	Units	Messages	Words
Bazaar (week1)	42	38	242	6,069
Bazaar (week2)	42	37	377	3,124
Forums (week1)	124	200	200	8,108
Forums (week2)	101	200	200	13,401
Twitter (week1)	77	100	100	1,663
Twitter (week2)	73	100	100	1,740

For our analysis we sampled from communication data in three streams, namely, the Bazaar chats, the Forum posts, and the Twitter tweets. It was our goal to sample in a way that would give us broad exposure across students and weeks in an unbiased way. From the discussion forums, we randomly sampled 200 posts per week after filtering out any messages posted by instructors or staff. Tweets have been collected using the TAGS Twitter Archiver, which was configured to retrieve all tweets containing the *#dalmooc* hashtag that identifies tweets pertaining to the course. In interest of broad sampling, for each user, we kept at most two tweets and removed all tweets by instructors or staff. We also removed duplicates and retweets. From the resulting set of tweets, we selected 100 contributions per week. For the chat data, in order to identify a unit with approximately as much content as the discussion posts, we chose as a unit of analysis a chunk of conversation occurring between two agent prompts, where each of these agent prompts was designed to start a new topic of conversation. Within each chunk, we considered all of the contributions belonging to the same speaker as a single unit, although we interpreted it within context. In interest of broad sampling, we chose to sample one chunk per chat transcript and disregarded all chats with less than two students (e.g. conversations between a single student and the agent). However, in some chunks, only one speaker spoke, which explains why the number of units is sometimes less than 42. Due to the lower number of chats in the second week of the course, we sampled 21 chunks per week in order to have an even distribution across weeks.

Data coding

Table 2: Descriptive statistics over coded data

	Social	Course Process	Course Content	Reasoning
Bazaar (week1)	18 (47.4%)	23 (60.5%)	14 (36.8%)	26 (68.4%)
Bazaar (week2)	22 (57.9%)	7 (18.9%)	21 (56.8%)	22 (59.5%)
Forums (week1)	39 (19.5%)	88 (44.0%)	53 (26.5%)	62 (31.0%)
Forums (week2)	32 (16.0%)	88 (44.0%)	80 (40.0%)	67 (33.5%)
Twitter (week1)	19 (19.0%)	31 (31.0%)	38 (38.0%)	28 (28.0%)
Twitter (week2)	7 (7.0%)	38 (38.0%)	57 (57.0%)	35 (35.0%)

In order to get a sense for the differences in the discourse occurring within our three communication contexts, we coded each contribution along two dimensions. The first dimension used three thematic distinctions to enable us to identify talk segments pertaining to three primary purposes, which were not treated as mutually exclusive: Social, Course Process, and Course Content. Social segments were ones where students worked to

create social connections with one another by sharing personal information, including contact information for further interaction. Course Procedure segments were ones in which the structure of the course, the course environment, or course procedures were discussed. And finally, Course content segments were ones in which the conceptual content of the course was substantively discussed. In order to locate discussion that potentially contributes to content learning, the primary relevant discussion would focus on that content. Under this heading, students may be reflecting on what they have learned or answering one another's questions. Discussion of course procedures is important for helping students cope when they are struggling with technical problems like finding resources, installing software, or navigating the courseware. Most of these contributions could be viewed either as exchange of help, or at least calling out for help. For example, even complaints about confusion regarding course procedures could be viewed as indirect requests for help. Thus, we may loosely consider segments coded this way as help-exchange related contributions. Making social connections also plays a valuable role in community building and provision of emotional support. Since some contributions mix these three foci, we coded this dimension as a set of three binary indicators applied separately to each contribution. In order to be beneficial for content learning, it is important to identify the manner in which content is discussed, and not just that it was mentioned. Thus, we coded a second dimension that distinguishes segments in which reasoning is articulated and therefore made public from those in which it is not. For this, we adopted a previously validated operationalization (Gweon et al., 2013). Each segment was coded either as displaying reasoning or not. With these two distinctions taken together, we can observe help related exchanges focusing on course procedures by looking at the frequency of discussion about course procedures, and we can observe opportunities for substantive reflective discussion about course content by identifying those segments related to course content where reasoning is articulated.

Participation analysis

In order to assess the extent to which our three Communication contexts (e.g., the edX discussion forum, the integrated Bazaar Collaborative Reflection tool and Twitter) engaged different users and in different types of talk, we examined the population of students who participated in each as well as the overlap between pairs of contexts. Ultimately, we are interested both in the distinctions between student populations with these contexts as well as how students connect across platforms in order to learn how these different communication spaces are already interconnected organically. This will inform our future efforts in providing explicit support beyond the borders of single communication platforms.

The Bazaar tool for collaborative reflection was part of an intervention that particularly requested pairs of students to reflect on the course content in a collaborative manner. Consequently, what we hoped to see in the chats was a constructive dialog in which the students revisit the topic of the week, gain a deeper understanding of the subject matter, connect the new knowledge with their personal experiences and exchange ideas. Forums are asynchronous communication tools and posts are not technically restricted to a certain length. Therefore, we expected the forum posts to constitute the largest amount of text compared to chats and tweets. In contrast to public communication platforms, such as Twitter, the target audience of forums is the community of students and instructors, both of which influences the content focus of the posts as well as the way they are written. In contrast to chats and forums, Twitter is an external microblogging service that openly broadcasts to the public. Users can post messages of up to 140 characters on their Twitter stream. At the same time, these messages are displayed in the streams of all followers of the original poster. Tweets can be marked with hashtags, which allows tweets with similar tags to be aggregated. The students in our MOOC were encouraged to use the *#dalmooc* hashtag in all course related tweets in order to engage other students or interested individuals in a discussion without them having to be followers of the poster. This hashtag was also used to sample the data for the purpose of our analysis. An interesting situation arises from the fact that posting a tweet with the course hashtag reaches both the people who are actively looking out for posts with this tag but also all the followers who are generally interested in the posts from this user but do not necessarily belong to the course in-group.

Findings

Quantitative analysis of participation across communication contexts

In order to quantify the overlap between the sets of users of each communication context, we attempted to map each contribution to an edX account and then compute the intersection of the resulting lists of users from each platform. Forum users can directly be identified in the edX logs and are therefore fully accounted for in our analysis. Bazaar chat users were able to log into the lobby with arbitrary screen names. We therefore use the edX clickstream logs to map each Bazaar user to an edX account. In some cases, it was not possible to compute the match because students did not enter the chat directly through the edX platform. Tweet authors were mapped

to edX accounts via voluntary information provided in user profiles from an additional social communication channel integrated in DALMOOC.
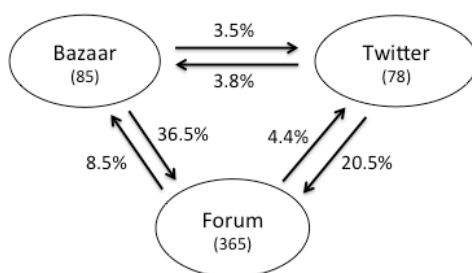

Figure 2. Overlap and distinction between subsets of participants in the Bazaar chats, Twitter, and discussion forums

The diagram in Figure 2 shows the relative overlap in users between pairs of social contexts. The numbers in the ovals represent the number of users whose edX ID could be matched with an ID from the associated context. The links represent the overlap. For example, 20.5% of all Twitter users we could map to edX accounts (78) also posted to the discussion forum while 4.4% of the forum users also posted on Twitter. This analysis suggests that, while we observe some overlap between subpopulations of students who participate in these contexts, the subpopulations are largely distinct.

Quantitative analysis of communication content and type

We hypothesized that students view the purpose of communication in the three contexts in different ways that would influence both the content focus and the nature of the discussion e.g., the extent to which we would observe students articulating their reasoning. We also hypothesized that the content focus of the discussion itself would influence the nature of the discussion as well.

In order to get a sense of the difference in content focus across the three contexts, we performed a chi-squared test, with Communication context and Week as the independent variables and each of the binary content focus variables as dependent variables. We also included the interaction between Communication context and Week. There was a main effect of Communication context on concentration of Social segments χ^2 (2, n=675) = 50.6, p < .0001 such that there was a significantly higher concentration of Social talk in the Bazaar chats than the other two contexts. There was a significant interaction between Communication context and Week χ^2 (2, n=675) = 6.42, p < .05 such that in Twitter, there was less social talk in week 2 than in week 1, but this did not generalize to the other two contexts. For Course processes, we observed a significant effect of Week χ^2(1, n=675) = 6.27, p < .05 such that there was a lower concentration of talk about Course procedures in the second week. We also observed a marginal effect of Communication context χ^2 (2, n=675) = 5,37, p < .05 such that there was somewhat less of a concentration of Course Procedure talk in the discussion forums than in Twitter, with Chat in between the two. There was also a significant interaction between Communication context and Week χ^2 (2, n=675) = 14.7, p < .001 such that the reduction in Course procedures talk was mainly in the Chat, with slight increases in the other two contexts. For Course content, there was a main effect of Week χ^2 (1, n=675) = 14.0, p < .001 such that there was a higher concentration of discussion pertaining to Course context in the second week of the course than the first across contexts. There was a main effect of Communication context χ^2 (2, n=675) = 13.6, p < .005 such that there was a higher concentration of Course content related talk in the Chats and Twitter than the Forums. There was no interaction between Week and Communication context.

Since we observed interactions between Communication context and Week on the three content foci, when we examined the relationships between Communication contexts and concentration of Reasoning, we considered also interactions with Content focus and Week. Thus, each model contains Communication context, Week, one of the Content focus variables, all two way interaction terms, and the three-way interaction term as independent variables. The dependent variable was Reasoning. In all three models, there was a significant effect of Communication context such that there was a higher concentration of Reasoning in the Bazaar Chats than the other two communication contexts. And there was never a significant main effect of Week or interaction between Communication context and Week. A simple model with Communication context as the independent variable and Reasoning as the dependent variable was also significant, so we report that test here χ^2 (2, n=675) = 28.4, p < .0001. There was no significant main effect of Social talk on Reasoning, but there were main effects of the other two binary content focus variables. In the case of Course content χ^2 (1, n=675) = 41.4, p < .0001 there was a higher concentration of reasoning in segments pertaining to Course content than those that did not have this. There was also a significant main effect of Course Procedures χ^2 (1, n=675) = 9.25, p < .05 such that there

was a higher concentration of Reasoning in segments pertaining to Course Procedures than those without. However in this case there was a significant two-way interaction between Week and Course Process χ^2 (1, n=675) = 11.5, p < .001 such that in Week1 there was a higher concentration of Reasoning when Course Process was being discussed, but this was not true in Week2. There was also a significant three way interaction between Week, Course process, and Communication context such that in Week2 there was a higher concentration of Reasoning in the Forums when Course process was discussed than not, but not in Week1.

Qualitative analysis

As we have shown in our quantitative analysis before, chat conversations show the highest average of reflective contributions across all the platforms we observed. An even more interesting difference lies in the way the course content is reflected in the chats. The one-on-one conversations in Bazaar exhibit a strong constructive character where reflective statements are not merely precompiled by each student and then exchanged, they are rather collaboratively constructed in the course of the conversation. The following short excerpt from a longer Bazaar chat shows such an interactive reflection. Rather than each student providing a single complete reply to the agent question, the students construct a joint reply by building on each other's contribution in their own reflection.

Agent	Let's start by looking at the logic of analytics, namely, how we use data to understand the world. Did this resonate with you? What are your concerns with this worldview?"
Student 1	Well this seems like a great place to start... you will meet a supervisor somewhere in this course i expect... using data is much more reassuring than working on solely intuition... on the other hand, it may be limiting to work with only things you can capture in numbers...
Student 2	yes, that's my thinking too, often real phenomena are oversimplified with numbers we should gather data also for example affective data etc
Student 1	but the pattern of working with data can be made more playful, juxtaposing different elements which might appear unrelated, and working to ask questions, as opposed to providing answers... by affective data, what do you mean?
Student 2	for example, asking about learners emotions during learning

While the segments pertaining to building social connections did not have any specific significance with respect to engendering articulation of reasoning, it is notable the extent to which students use each communication medium to reach out to other for social connection, often with the apparent desire to continue to interact over the course. In the chat, this was especially evident in longer discussions with a lively exchange of ideas.

Student 2	Very enjoyable session, thanks for the picture... can you give me a link to your blog or some other means of getting back in touch please? maybe we will do some other activity at some point further along? how are you getting along with tableau? do you have data?
Student 1	@HANDLE at twitter and i also started a course blog http://URL
Student 2	cool, thanks.... USER@DOMAIN.COM for me...

While the requests to connect expressed in the chats are much more personal and based on a positive exchange of ideas, the forums serve more as a market for people to find other like-minded students with similar interests or from similar backgrounds.

Discussion and current directions

In this paper we have described an analysis of data from one cycle of a design based research process in which we aim to engage students in more intensive discussion based interactions in Massive Open Online courses. We compared across three communication contexts, including Twitter, threaded discussion forums, and synchronous collaborative chats. What we find is that different subpopulations of learners within DALMOOC, an edX MOOC that is the focus of this study, tended to gravitate towards different ones of these contexts. Furthermore, each context was associated with its own unique profile in terms of content focus and the nature of the discussion (i.e., concentration of articulation of reasoning). We see ample evidence within contributions across media pertaining to social connection that these MOOC learners crave continuing social engagement with

other individuals participating in their MOOC course. The analysis suggests that there is value in providing a diverse set of discussion contexts but that it creates a need for greater efforts towards effective bridging between media and channeling of students to pockets of interaction that are potentially of personal benefit. Thus, while providing an eclectic combination of communication contexts has value in terms of engaging a wider variety of MOOC learners, it appears to exacerbate the problem of students who report being overwhelmed by the amount of communication in the forums and having trouble finding the places where there is interaction with the content focus and style they are comfortable with. Together these results suggest a research agenda going forward that seeks to design methods for greater orchestration across media. While some recent work develops social recommendation approaches that operate within single communication media, such as discussion forums (Yang et al., 2014), much work is left to do to develop more effective bridging and integration across media.

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