Positive Impact of Collaborative Chat Participation in an edX MOOC

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Abstract. A major limitation of the current generation of MOOCs is a lack of opportunity for students to make use of each other as resources. 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. In this paper we evaluate an intervention that makes synchronous collaboration opportunities available to students in an edX MOOC. We have implemented a Lobby program that students can access via a live link at any time. Upon entering the Lobby, they are matched with other students that are 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. Results of a survival model in which we control for level of effort suggest that having experienced a collaborative chat is associated with a slow down in the rate of attrition over time by a factor of two. We discuss implications for design, limitations of the current study, and directions for future research.

Keywords: Collaborative reflection · Survival analysis · Massive open online courses

1 Introduction

The rise of Massive Open Online Courses (MOOCs) has been the subject of a great deal of hype followed by almost as much disappointment. Some of the biggest limitations are related to the human side of effective educational experiences. In contrast, the field of Computer Supported Collaborative Learning (CSCL) has a rich history extending for nearly two decades, covering a broad spectrum of research related to learning in groups, especially in computer mediated environments. In this paper we describe the initial stages of a research program designed to import findings from a history of successful classroom research in the field of CSCL to the challenging environment of MOOCs.

Effective collaborative learning experiences are known to provide many benefits to learners in terms of cognitive, metacognitive, and social impact (Kirschner, Paas, & Kirschner, 2009; Webb & Palinscar, 1996). These experiences offer a potentially valuable resource for MOOCs, if affordances can be provided that facilitate high quality collaborative learning interactions in the absence of human facilitators that can

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keep up with the high enrolment in such courses. In this paper, we build on a paradigm for dynamic support for group learning that has proven effective for improving interaction and learning in a series of online group learning studies conducted in classroom settings. In particular we refer to using tutorial dialogue agent technology to provide interactive support within a synchronous collaborative chat environment (Kumar et al., 2007; Chaudhuri et al., 2008; Chaudhuri et al., 2009; Kumar et al., 2010; Ai et al., 2010; Kumar & Rosé, 2011). Introduction of such technology in a classroom setting has consistently led to significant improvements in student learning (Adamson et al., 2014), and even positive impacts on the classroom environment outside of the collaborative activities (Clarke et al., 2013). While it would seem to be desirable to import such technology into a MOOC setting to provide a learning experience that is both more instructionally valuable and socially supportive, such an introduction comes with it technical, methodological, and theoretical challenges. In this paper we present an early design for integration of this technology with the edX platform and results from a first deployment study. We provide an analysis of findings, which culminates in a vision for an ongoing research program.

2 Motivating Synchronous Collaboration in MOOCs

Tutorial dialogue agents have already achieved substantial impact in the field of CSCL. In that context, it has been noted that in order to support the growth of student discussion skills, it is necessary to design environments with affordances that encourage transactive discussion behaviors and other valuable learning behaviors. The most popular approach to providing such affordances in the past decade has been that of script-based collaboration (Dillenbourg, 2002; Kollar et al., 2006; Kobbe et al., 2007). The early non-adaptive scripting approaches described above can sometimes result in both over-scripting and in interference between multiple scripts (Weinberger et al., 2007), both of which have been shown to be detrimental to student performance. More dynamic approaches can trigger scripted support in response to the automatic analysis of participant activity (Soller & Lesgold, 2000; Erkens & Janssen, 2008; Rosé et al., 2008; McLaren et al., 2007; Mu et al., 2012). This sort of analysis can occur at a macro-level, following the state of the activity as a whole, or it can be based on the micro-level classification of individual user contributions.

The collaborative tutoring agents described by Kumar and colleagues (Kumar & Rosé, 2011; Kumar et al., 2007) were among the first to implement dynamic scripting in a CSCL environment. In that work, the role of the support was to increase the conceptual depth of discussions by occasionally engaging students in directed lines of reasoning called Knowledge Construction Dialogues (KCDs) (Rosé & VanLehn, 2005) that lead students step by step to construct their understanding of a concept and how it applies to the collaborative problem solving context. These encounters were triggered in the midst of collaborative discussions by detection that students were discussing an issue that is associated with one of the pre-authored interactive directed lines of reasoning. Thus, these interventions had the ability to be administered when appropriate given the discussion, rather than being triggered in a one-size-fits-all fashion. In an initial evaluation (Kumar et al., 2007), this form of dynamic support was associated with higher learning gains than a control condition where students had access to the same lines of reasoning, but in a static form. In a subsequent study, students were found to gain significantly more if they had the option to choose whether or not to participate in the directed line of reasoning when it was triggered (Chaudhuri et al., 2009). Scripting such as this offers the potential for minimal interventions to be used more precisely and to greater effect, with the hope of greater likelihood of students internalizing the support's intended interaction patterns. Further, the benefits of fading support over time (Wecker & Fischer, 2007) might be more fully realized, as the frequency of intervention could be tuned to the students' demonstrated competence.

Now that this positive impact of tutorial dialogue agents within the field of CSCL has been established, a valuable next step could be to import this positive effect in the context of MOOCs. A particular challenge of this transfer is the relatively high attrition rate in MOOCs. If students drop out before they have the chance to experience a valuable learning experience, then they will not have the opportunity to benefit from the offered materials. Thus, in this work, we ask the question of whether experience of a collaborative chat supported by a tutorial dialogue agent has the effect of slowing down attrition over time in a MOOC.

The MOOC environment presents a number of challenges that must be addressed in order to introduce synchronous collaboration opportunities, but chief among them is the tremendous coordination challenge. In a MOOC, students may come and go as they please, and since they may be logging in from anywhere, any number of events could interfere with the task proceeding as planned: some students may have different preferences regarding which activities within a task to spend more or less time on, or a student may be called away from the computer, the internet connection may drop, or a student may give up and drop out in the middle of the activity. Furthermore, the sheer numbers of students make it challenging to coordinate plans for meeting times.

3 Technical Approach

As a first step towards achieving a positive impact of CSCL technology in MOOCs, we integrated a collaborative chat environment with interactive agent support in a recent 9-week long MOOC on learning analytics (DALMOOC) that was hosted on the edX platform from October to December 2014. Overall, 21,941 students enrolled in the course. The median age was 31 with 24.8% of the students 25 and under, 50.4% between 26 and 40 and 19.2% over 40. 180 countries were represented in the course with the majority of students from the USA (26%) and India (19%). A self-selected subset of students attempted participation in collaborative reflection activities that were offered each week as enrichment activities subsequent to individual learning activities.

In the following, we will describe the integration of our chat environment in DALMOOC. 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. The Lobby introduces an intermediate layer between the edX platform and the synchronous chat tool. Even though the Lobby allows groups of arbitrary sizes to be formed, we decided that agent-guided discussions in groups of two students are the most suitable setup. Students enter the Lobby with a 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 but did not enforce a couple of two hour time slots during each week of the MOOC when students might engage in the collaborative activities. These timeslots were advertised in weekly newsletters.

Upon entering the Lobby, students were asked to enter their screen name. Once logged into the lobby, the student waited to be matched with another participant. If they were successfully matched with another learner who arrived at the Lobby within 10 minutes, they and their partner were presented with a link to a chat room created for them in real time. Otherwise they were requested to come back later. A visualization was presented to them that illustrated the frequency of student clicks on the button at different times of the day on the various days of the week across a variety of time zones so that they would be able to gauge when would be a convenient time for them to come back when the likelihood of a match would be higher.

The chat setup had been used in earlier classroom research (Adamson et al., 2014). It provides opportunities for students to interact with one another through chat as well as to share images. The chat environment furthermore has built-in support for conversational agents who appear as regular users in the chat. In DALMOOC, the tutorial dialogue agents led the pairs of students through collaborative reflection activities that prompted them to share their thoughts about the learning activities they had engaged in individually before entering the collaborative reflection. A separate Lobby and chat instance was set up for each week of the course, and in each chat instance the agent was configured to scaffold discussion about the central topic of the respective week. Both the Lobby software and the chat tool logged any interactions that occurred between the students or between the students and the system. Overall, 371 unique students participated in the chat activities during the first two weeks of the course. They posted 4,624 messages in 215 chat sessions with a total of 58,325 tokens. The average duration of a chat was 15 minutes.

Integrating a synchronous collaborative activity in an inherently asynchronous learning environment that is used by students in different time zones from all over the world was one of the greatest organizational challenges to overcome. As mentioned earlier, we attempted to alleviate the problem by introducing dedicated chat hours to increase the likelihood of students getting matched with each other. Nevertheless, frequently students who entered the Lobby could not be matched with a chat partner within 10 minutes. The high percentage of students who waited until the Lobby asked them to return at a later point in time is however a good indicator that the students are motivated to participate. 257 students returned at least once to the Lobby while individual students logged in up to 15 times in a given week.

4 Evaluating the Impact of Participation on Attrition

In order to measure the strength of association between participation in a collaborative chat and attrition, we use a survival analysis. Survival analysis is a statistical modeling technique used to model the effect of one or more indicator variables at a time point on the probability of an event occurring on the next time point. In our case, we are modeling the effect of participation in a collaborative chat on probability that a student ceases to participate actively in the course on the next time point. In DALMOOC, students participated in chat sessions that were offered in each of the first 6 weeks of the course.

4.1 Methodology

Survival models are a form of proportional odds logistic regression, and they are 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 ceased their participation at the time of the analysis but might at some point subsequently). The survival models we employ in this study make a prediction about the probability of an event 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 (in our case, student dropout) occurring increases or decreases with an increase or decrease in the associated predictor in the case of a numeric predictor, or presence vs. absence of the factor in the case of a binary variable. A hazard ratio of 1 means the factor has no effect.

If the hazard ratio is a fraction, then the factor decreases the probability of the event. For example, if the hazard ratio was a number of value .4, it would mean that for every standard deviation greater than average the predictor variable is, the event is 60% less likely to occur (i.e., 1 - n). If the hazard ratio is instead greater than 1, that would mean that the factor has a positive effect on the probability of the event. In particular, if the hazard ratio is 1.25, then for every standard deviation greater than average the predictor variable is, the event is 25% more likely to occur (i.e., n - 1).

Survival analyses are correlational analyses, and as such they do not provide causal evidence for an effect. However, lack of an effect in a survival analysis would suggest that the data fail to provide causal evidence as well. A positive effect in a survival analysis would suggest that it makes sense as a next step to manipulate the associated factor so that causal evidence for a positive effect could be measured.

4.2 Specifying the Model

In our survival model we include control variables, independent variables, and a dependent variable. Our primary interest is in how the independent variables related to participation in collaborative chats make predictions about the dependent variable, which indicates course dropout. However, control variables are essential. They allow us to account for factors other than the factors of interest that may influence attrition so they do not bias the results. For example, some students start the course with a greater commitment to active participation, and factors associated with higher a priori commitment are typically associated with slower attrition over time (Wen et al., 2014; Wang et al., 2012). If we do not account for this in control variables, then the independent variables that differ in value depending on the a priori commitment level of students will have results that confound the factors of interest with a priori commitment.

Unit of Analysis. In order to assess the impact of measured factors at each time point during a student's trajectory through the course, it is necessary to decide what the unit of analysis is. In other words, it is necessary to determine how much time each time point should represent. Even the most active participants in the course did not participate every day. However, very active participants returned to the course more than once within a week. Thus we adopted a span of two days as the length of each time point. Since our analysis spans 6 weeks of time, we estimate the probability of retention in the course at each of 21 time points in our analysis.

Student Population. In order to participate in a chat, a student had to attempt to be matched for a chat by clicking on the button to enter the Lobby. In DALMOOC, while there were over 20,000 students who enrolled in the course, most of these students were not active participants. In any given week, only between 1,181 and 6,379 students logged into the course with a median of 1,920 over the full 9-week runtime of the course. The collaborative chat activities were positioned as enrichment activities after the individual work for the week was completed. Thus, students who attempted to be matched for a chat were on average more active and more committed to the course than students who did not. We would expect a variable that indicates that a student made at least one attempt to be matched during a time period would be associated with lower attrition. As discussed above, however, these attempts did not always result in a successful match due to a lack of critical mass of students at many times. Frequently in order to be successfully matched for a chat, students had to click to enter the Lobby at many different times. Failing to be matched for a chat was discouraging to students, as evidenced by complaints mentioned in the discussion forums. And we would expect that larger numbers of attempts would be associated with more and more frustration, and therefore, higher attrition. Thus, we expect these two potential independent variables of interest to be associated with opposite effects, although the variables themselves would necessarily be correlated. In survival models it is important not to include multiple independent variables that are highly correlated. But including only one or the other is also problematic, since we expect that these are both important effects. In order to address these issues we only include in the survival analysis presented here the subset of students who during at least one time point clicked to enter the Lobby at least once. In that way we control for the elevated level of a priori commitment associated with the set of students who clicked to enter the Lobby at least once. Only 815 students attempted to be matched for a collaborative chat at least once during the 6 weeks when collaborative chats took place. Thus, the survival analysis we present in this paper is focused on these 815 students. To test the implications of this choice over the whole set of students who clicked in the course materials at least once, we verified that clicking to enter the Lobby at least once was associated with lower attrition whereas the number of clicks to enter the Lobby was associated with higher attrition.

Control Variables. Other indicators of commitment to active engagement were the number of clicks on course videos or number of clicks to access the discussion forums. We present the estimates for the model computed over the selected 815 students below using number of *Video Clicks* and number of *Forum Clicks* as control variables. Over the whole set of students, number of video clicks did not make a significant prediction about attrition, and number of forum clicks was associated with lower attrition.

Independent Variables. Since only the 815 students who clicked to enter the Lobby at least once were included in the analysis, it was not necessary to include that binary variable in the model as an independent variable. So we were able to include number of Lobby clicks, which we refer to as *Match Attempts*, as an independent variable, in order to quantify its hypothesized association with higher attrition. We also included a binary variable called *Match Success* that was true for students who were successfully matched for a chat during a time period in order to measure the hypothesized association between the experience of being matched for a chat and lower attrition. In order to measure a hypothesized mitigating effect on the negative impact of having to click many times to be matched if one is finally matched successfully, we included the interaction between these two variables in the model as well.

Dependent variable. The dependent variable we referred to as drop. This was a binary variable that was 1 during the last time point of a student's active participation in the MOOC and 0 otherwise. All of the continuous variables in the model were standardized in order to enhance the interpretability of the model estimates. In other words, the range of continuous variables was scaled so that the range had a mean value of 0 and a standard deviation of 1.

4.3 Survival Model Results

We hypothesized that we would find evidence that the experience of collaborative chats would be associated with lower attrition over time, and the results of the survival analysis support this hypothesis.

Table 1 presents the hazard ratios computed from the survival analysis. First we examine the estimated hazard ratios on control variables to make sure those effects make sense. The hazard ratio on Video Clicks indicates that elevated numbers of video clicks are associated with higher attrition rather than lower attrition, which was a surprise. When we examined the logfiles for the students included in the survival analysis, we noticed that virtually all of them had viewed all of the videos. Thus, elevated numbers of video clicks could distinguish students who were having trouble following the videos and needed to backtrack multiple times. The hazard ratio on Forum Clicks, .51, suggests that students with elevated numbers of clicks on the discussion forums, which occur either when students are reading the discussions or posting to the forums, was associated with a substantial reduction in attrition. In particular, it suggests attrition is reduced by half when students have a standard deviation higher number of forum clicks than average.

Now we turn to an examination of the hazard ratios on our independent variables. As hypothesized, elevated numbers of Match Attempts are associated with higher attrition. In particular, a hazard ratio of 2.33 indicates that students who have an elevated level of Match Attempts at a time point are 133% or 2.33 times more likely to drop out at the next time point. This suggests a substantial negative effect of the frustration at sometimes having to try multiple times to get matched for a chat. However, the hazard ratio on Match Success suggests a substantial reduction of attrition when a student experiences a match with another student. In particular, a hazard ratio of .44 suggests that students who experience a match are 56% less likely to drop out at the next time point than students who did not experience a match success. The interaction term is also associated with a fractional hazard ratio. In particular, a hazard ratio of .76 suggests that over and above the generally positive effect of experiencing a match, the experience of a match after having made multiple attempts partly mitigates the negative effect of the multiple attempts, in particular, reducing attrition by 24%. The survival curves that display visually the difference in attrition over time of students who experience a match vs. students who do not experience a match is displayed in Figure 1.

Table 1. Survival table with estimates that measure the impact of control variables (Video Clicks and Forum Clicks), and independent variables (Match Attempts, Match Success, and the interaction between the two) on probability of survival from one time point to the next

Independent Variable	**Hazard Ratio**	**p-Value**
Video Clicks	2.38	$p < .0001$
Forum Clicks	0.51	$p < .0001$
Match Attempts	2.33	$p < .0001$
Match Success	0.44	$p < .01$
Interaction between Attempts and Success	0.76	$p < .05$

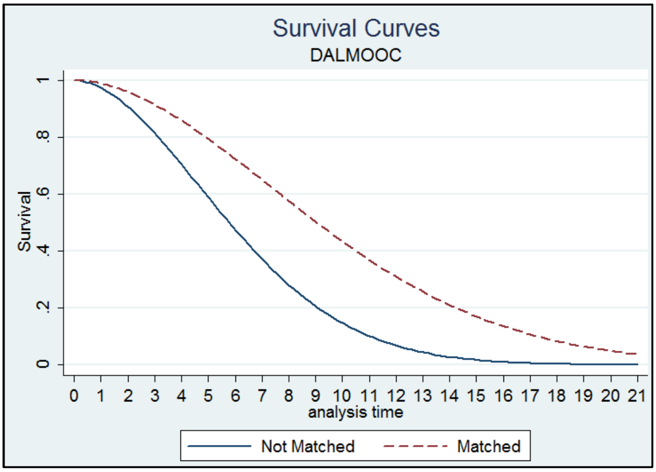

Fig. 1. Survival curve that graphically illustrates how much less likely to drop out at each time point a student is if they experience a match for a synchronous collaboration at that time point

5 Discussion and Conclusions

In this paper we have evaluate an intervention that makes synchronous collaboration opportunities available to students in an edX MOOC. The results suggest a substantial reduction in attrition over time when students experience a match for a synchronous collaborative reflection exercise. Nevertheless, these results must be treated with some caution as we experienced significant difficulty in managing the logistics of matches. Even with 20,000 students enrolled in the course, some students had to make as many as 15 attempts to be matched with a partner before a match was made. Because the results suggest that students found value in the experience, it appears to be worth the effort to address this challenge in future work. One potential direction is to form matches during other course activities that extend over time, such as a video lecture. Students could simultaneously be waiting for a match and watching a video. In that case, students may experience more success at matches since the wait time would be longer on average. And furthermore, there may be less negative impact of not getting matched on an attempt since students would be doing something productive while waiting.

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