# When Optimal Team Formation Is a Choice - Self-selection Versus Intelligent Team Formation Strategies in a Large Online Project-Based Course

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**Abstract.** Prior research in Team-Based Massive Open Online Project courses (TB-MOOPs) has demonstrated both the importance of effective group composition and the potential for using automated methods for forming effective teams. Past work on automated team assignment has produced both spectacular failures and spectacular successes. In either case, different contexts pose particular challenges that may interfere with the applicability of approaches that have succeeded in other contexts. This paper reports on a case study investigating the applicability of an automated team assignment approach that has succeeded spectacularly in TB-MOOP contexts to a large online project-based course. The analysis offers both evidence of partial success of the paradigm as well as insights into areas for growth.

**Keywords:** Automated team formation · Transactivity
Team-Based Massive Open Online Project Course · TB-MOOP
Peer learning

## 1 Introduction

Effective collaborative learning experiences are known to provide many cognitive, meta-cognitive and social benefits to learners [14,26]. Several MOOC studies have tried to replicate the successes that peer learning has had in offline contexts but have been met with mixed results. Attempts to encourage unstructured discussions using real-time chat did not find improvements in students' retention rate or academic achievement [5] whereas chat facilitated by an intelligent agent led of an approximately 50% reduction in dropout [7].

Early work on Massive Open Online Courses (MOOCs) revealed that although online students call for more social interaction, peer learning opportunities fail without support [15]. Students may fail to provide feedback on the work of their peers; they may not show up for a discussion session they signed up for; or they may quit working with their team altogether as they drop out of the


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course [15]. Learners have reported facing more frustration with groups formed online than in face-to-face learning environments [21]. Simply providing communication technology has also proven insufficient. For example, an early MOOC that offered optional learning groups found that only 300 out of a total of 7350 participants in the course signed up for one of the 12 learning groups [16]. One explanation is that students don't fully recognize the role that social interaction is meant to play in their learning. It has thus become clear that offering effective social interaction in MOOCs is a research problem in its own right [22]. In this paper, we investigate a particularly challenging aspect of this broader agenda, namely supporting team-based project learning at scale in online learning environments.

While the bulk of the research on introducing social interaction opportunities are either as informal discussion forums or short-term chat activities, some recent work, including our own past work, takes on the more ambitious challenge of importing team-based projects into MOOCs [24,27,28]. Team projects are common in face-to-face courses, however, from the beginning of the MOOC movement, there has been skepticism about whether such forms of learning would work in MOOCs. One of the many challenges cited has been the difficulty of forming well-functioning teams [8,17,30]. In the MOOC context, prior work has addressed the problems of forming effective teams and supporting coordination and interaction within teams once they are formed. Work on team formation has investigated what evidence can be identified in the behavior traces of students that can be used to do the team formation, ideally in an automated fashion [9,19,20,29,30].

In our work, we begin with a fully automated approach that has been successful in a large controlled lab study [28] as well as a 4 week MOOC [27]. While this empirically grounded paradigm has worked well in short term studies where stakes are low, it remains an open question whether the paradigm will hold up in a much longer course where stakes are higher. Specifically, it is essential to investigate how the idiosyncrasies of the context might affect the paradigms and further create more generalizable and scalable approaches that can be applied in a variety of contexts. This paper therefore provides a case study applying this successful paradigm [27] to a 16 week large online project course on Cloud Computing offered as a part of degree-granting programs by Carnegie Mellon University's (CMU) Open Learning Initiative (OLI) on 3 CMU campuses. Our analysis provides evidence of partial success and several insights into how the paradigm might need to be adapted for this new context.

In the remainder of the paper we first describe past work on team formation in at-scale learning environments. Next, we describe the context of the course in which the current study was conducted. The following section then describes the method and experimental setup. We then describe our experiments and the results we obtained. We conclude with a discussion of our findings and future work.

## 2 Past Work on Automated Team Formation

Algorithmic team formation approaches that have emerged have seen both successes and failures. Attempts at providing support for team formation have sparked research on criteria that leads to better teams and algorithms that can then optimize over those criteria. Many automated approaches to team formation base their team assignments on characteristics of individual learners such as learning style, personality or demographic information [6]. This information however needs to first be assessed or discovered before it can be provided to the algorithm for optimization. Therefore, these approaches are often not feasible in typical online course environments. Further, forming teams based on typical demographic features such as gender and time zone has not been shown to significantly improve team engagement or success in MOOCs [30].

Approaches to automated team formation that have succeeded have focused on inducing buy-in among the participants. Opportunistic group formation for instance [12], triggers a negotiation process between learners to form groups once it detects that the learners can move from the individual learning phase to the group learning phase. The negotiation process allows learners to be assigned to roles based on their learning goals and the goals for the whole group thus creating buy-in. The approach showed that learners using the framework performed as well as students in face-to-face situations. Another such successful strategy has made use of a collaborative process measure called transactivity, which can be defined as the reasoning of one utterance building off or operating on the reasoning of another utterance [4]. The construct of transactivity stems from a Piagetian learning paradigm where it is believed to flourish in social settings that have a balance of respect and a desire to build common ground. Groups that exhibited high transactivity were shown in previous studies to be associated with higher learning [23], higher knowledge transfer [10] and better problem solving [3].

In the case of team formation, it is the social underpinnings, the signal of mutual interest and respect that a transactive exchange entails that renders this construct an estimate of collaboration potential between students. The automated strategy makes use of evidence of transactive exchanges in a whole course online discussion process that happens prior to the team activity. The resultant teams were shown to perform better than random teams first in a synthetic environment on Amazon Mechanical Turk [28] and then externally validated in a Team-Based Massive Open Online Project-Based (TB-MOOP) course offered on edX [27].

## 3 Course Context and Intervention

The Open Learning Initiative[1] (OLI) Cloud Computing Course is a semester-long completely online course offered to Carnegie Mellon University (CMU) students on its various campuses[2]. The fall 2017 semester offering of the course

[1] http://oli.cmu.edu/.
[2] http://www.cs.cmu.edu/~msakr/15619-f17/.

saw participation from three CMU campuses - Pittsburgh, Silicon Valley and Rwanda. In past offerings of the course, students were required to complete 10 individual projects and then self-select into teams for a 7 week team project. Students complete conceptual topics and assessments on the OLI platform and use a homegrown platform, TheProject.Zone[3] to complete individual and team programming projects. There is no lecture to attend, so students do not have the opportunity to meet face-to-face as part of the course. However, students at the same campus may have encountered each other face-to-face outside of class, and all students in the course do interact with the teaching staff and with other students on Piazza[4], a question and answer forum. The course has been offered 9 times before, so students came in with the expectation that they need to form a team for the group project. Many students started forming teams on their own from the beginning of the semester.

In order to introduce Transactivity-Based matching for team formation in the course, we needed to make two adjustments to the course practices. First, during the initial part of the semester when students were working through their ten individual project assignments, they were required to post a reflection to the discussion forum after each project and offer feedback to three other students. This feedback exchange provided both the opportunity for students to experience more social interaction in the course as well as provide the data for estimating collaborative potential for pairs of students based on their exchange of transactive feedback contributions. We refer to this repeated reflective exchange henceforth as the Reflection-Feedback Setup. An automated measure of transactivity exchange between students in this context is then used to estimate pairwise collaboration potential, and then a constraint satisfaction algorithm is used to assign teams in such a way that students are more likely to be part of teams with the other students they have interacted with transactively than those they have not interacted transactively with. The second adjustment was that rather than asking students to find their own teams, which is what had been done in the past, in this offering we provided automated recommendations for team assignment based on the Transactivity-Based matching algorithm. However, we did not force students to take the recommendations. Instead, we provided these as suggestions with the idea of observing the extent to which receiving recommendations would be viewed as attractive to students.

### 3.1 The Reflection-Feedback Setup

As mentioned, after each individual project, students reflected on their projects by answering questions similar to those shown below:

- Pick a task you found most challenging. Why was it challenging and how did you end up solving it?
- Pick a task and choose among different solutions paths for this task. What were the trade-offs you ended up making?

[3] https://theproject.zone/.
[4] https://piazza.com/.

– Describe how you tested one of the tasks. How did you design your test? Was your initial test sufficient? If not, how did you improve it?

Their answers were then shared to a discussion forum that the entire class could access and the students were encouraged to provide constructive feedback on these reflection posts. An example reflection, prompt and feedback post can be seen in Fig. 1. Substantive discussions resulted from this reflection-feedback

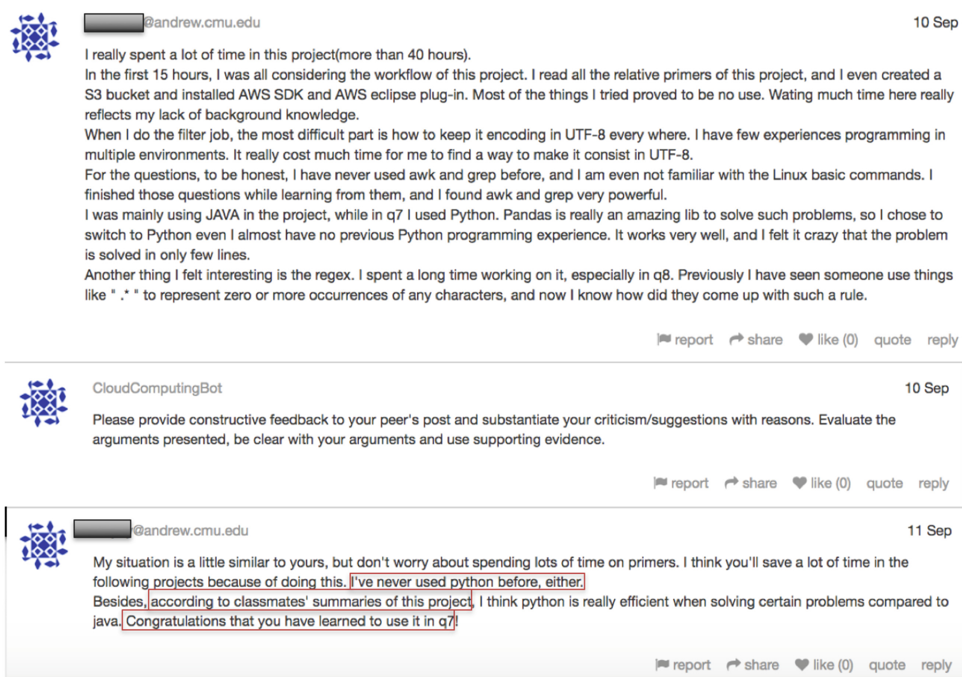


**Fig. 1.** Examples of a reflection post, a prompt soliciting constructive feedback and a feedback post. Feedback post highlights instances of common ground, synthesis and encouragement.

setup as shown in the example feedback post. These posts showed evidence of students synthesizing knowledge from several posts, achieving common ground and providing encouragement to each other. An example of a transactive and non-transactive exchange between students from this reflection-feedback setup is shown below:

– **Transactive Exchange**
  ***Student 1:*** *"...I used 'f.readlines()' to read the wiki log file. It worked well on my own computer, but it caused a 'MemoryError' when I tested it on AWS ..."*
  **Student 2:** *"The file object itself is a iterator. So if you 'for x in file', you get lines as x. This is a more pythonic way than using 'readline()'."*

– **Non-Transactive Exchange**
***Student 1:*** *"... I approached the problem by breaking it out into different modules and functions which made it possible to test different cases really fast. ..."*
***Student 2:*** *"Well done!"*

In the first case, the second student is referring explicitly to the reasoning of the first student and building on that reasoning further with their own reasoning. The interaction is therefore transactive. In the second case, the second student is referring to the reasoning of the first student but is not contributing original reasoning of their own and the interaction is therefore non-transactive. Evidence of transactive exchanges can thus be mined from these interactions to automatically inform our team formation algorithm.

### 3.2 Transactivity-Based Team Formation

Data from the feedback exchange in the discussion forums was used as input to the Transactivity-Based matching algorithm.

**Automatic Transactivity Analysis and Team Assignment.** Before an estimate of pairwise transactivity exchange can be computed, posts from the discussion forum must first be annotated as transactive or not. In our work, this was accomplished using a text classification approach developed in prior work on automated collaborative learning process analysis [2,13,28]. This approach requires training data including a validated and reliable coding of transactivity [11]. For our work, we used a previously validated coding manual [11] and coded 200 feedback exchanges by hand. Using this training data, we trained a model to perform the transactivity analysis over the whole set automatically.

Team assignment was based on behavior traces for the first five weeks of the course. By that point, students had completed 3 individual assignments and had written a total of 1007 discussion forum posts. For each pair of students, we computed the total number of threads where either they both contributed a transactive post to the discussion or one of them started the thread and the other contributed a transactive post. We refer to this quantity henceforth as the Pairwise Transactivity Score for this pair of students. Once the Pairwise Transactivity Score is computed for each pair of students, a team score can be computed by averaging the Pairwise Transactivity Score for each pair within the group. A score for the resulting teams across the whole class can be computed by averaging across the team scores. The goal of the automated team-matching algorithm is to assign students to teams in such a way that the score over the whole class is maximized. An exhaustive search would take inordinately long. Thus, a constraint satisfaction algorithm is used to find an approximate solution that comes close to the optimal assignment that maximizes the score across the class without having to do an exhaustive search. The specific constraint satisfaction algorithm we used is called the minimal cost max network flow constraint satisfaction algorithm [1]. The algorithm generally tackles the resource allocation problem with constraints and in prior work, role assignments such as the roles of a Jigsaw condition were used as constraints [28]. In this paper, location was used as the constraint in addition to maximizing average transactivity across teams i.e., all members of the team are to be located on the same CMU campus. This was because, based on past runs of the course, it was observed by the course staff that co-located teams worked better together and co-location was an expressed desire of students who had taken the course in the past also. The algorithm finds an optimal grouping within $O(N^3)$ time complexity where N is the number of students. A brute force approach would have O(N!) time complexity and would be infeasible in practice.

The algorithm is capable of forming teams of arbitrary size and approximates the solution in admissible time by maximizing the transactivity post count between two adjacent pairs of users instead of the total accumulated transactivity post count. A discussion network which is a directed weighted graph of the student's discussion in the reflection-feedback phase weighted by the transactivity score is built and the successive shortest paths algorithm shown in Algorithm 1 greedily finds the minimum cost flow until there is no remaining flow in the network.

**Algorithm 1.** Successive Shortest Paths for Minimum Cost Max Flow

$f(v_1, v_2) \leftarrow 0 \ \forall \ (v_1, v_2) \in E$<br>
$E' \leftarrow a(v_1, v_2) \ \forall \ (v_1, v_2) \in E$<br>
**while** $\exists \Pi \in G' = (V, E')$ s.t. $\Pi$, a minimum cost path from source to destination **do**<br>
    **for each** $(v_1, v_2) \in \Pi$ **do**<br>
        **if** $f(v_1, v_2) > 0$ **then**<br>
            $f(v_1, v_2) \leftarrow 0$<br>
            remove $-a(v_2, v_1)$ from $E'$<br>
            add $a(v_1, v_2)$ to $E'$<br>
        **else**<br>
            $f(v_1, v_2) \leftarrow 1$<br>
            remove $a(v_1, v_2)$ from $E'$<br>
            add $-a(v_2, v_1)$ to $E'$<br>
        **end if**<br>
    **end for**<br>
**end while**

The algorithm can be extended to accommodate more than one constraint but it should be noted that adding additional constraints could mean that an optimal team assignment ceases to exist.

### 3.3 Team Recommendation

At the end of Week 6, automated team assignments were formed using data from the reflection-feedback setup through Week 5 and then sent by the course instructor to the students who belonged to the same team over email. The email provided information to the students about how the teams were formed, what empirical evidence was used to form the teams and also served as their introduction to their teammates. Importantly, the email highlighted that the team assignments were only a recommendation and not a prescription from the course staff. An excerpt from the email is given below:

*"At this point in the semester, it is time to get organized into teams for the course team project work. Up until now, your work has been entirely individual, though you have shared it with the class community, and have offered each other feedback. Research in online team-based learning suggests that some aspects of interactions in a public class space signal collaboration potential. In particular, these aspects relate to expression of ideas and ways of evaluating the ideas and perspectives of others. Based on observation of your participation in the online feedback activities in this class, that prior research suggests you would work well together. Please consider this recommendation as you make your official declaration of team commitment for this course."*

Students were then asked to deliberate over these recommendations and their final team assignments were to be submitted on the TheProject.Zone. 35 total teams were formed with 23 teams in the Pittsburgh campus, 11 teams in the Silicon Valley campus and 1 team in the Rwanda campus. All suggested teams had 3 members each except the Rwanda team which had 2 members. Out of these 35 teams formed algorithmically, 5 teams took up our recommendation at least partially. A total of 27 teams survived till the end of the course with 7 teams of 2 members each and 20 teams of 3 members each.

At the end of the course, students filled out a post-course survey where they discussed their reasons for taking the recommendation or not.

## 4 Method

In this work we adopt a case study methodology to investigate how the Transactivity-Based team assignment paradigm plays out differently in a 16 week for-credit project course than in a 4 week MOOC, where it had been evaluated in the past. Here we discuss observations from the online discussion in the Reflection-Feedback Setup, the team formation processes that ensued after the Automated Team Assignment, and the subsequent team project work and set up for a quantitative analysis that is found in the Results section.

### 4.1 Measurement

**Auto and Manual Project Grade.** We measure the success of the teamwork in terms of the grade each team received on the final project. There were two aspects of the project, namely, an autograded portion of the software and a manually graded portion based on their report.

**Post-course Survey.** Students were given a post-course survey at the end of the semester. The survey contained three open response questions including: "What was most valuable to you and worked best in the team experience?", "What was least valuable to you and worked least well about the team experience?", "What criteria did you use to choose team members, and when did you begin that process?". From this data we coded three variables for each student, namely SelectionProcess, RelationalIssues, and DivisionOfLaborIssues. We coded SelectionProcess as a nominal variable with the following values: *Know* if students indicated selecting people they knew already, *Recommendation* if students indicated taking the recommendation, *Observation* if students indicated making a selection based on their observations on the course platform, and *Generic* if they did not indicate how they found their team. RelationalIssues was coded as a numeric variable with score 1 if they mentioned something positive about relationships in their group, −1 if they mentioned something negative about relationships in their group, and 0 otherwise. Similarly we coded DivisionOfLaborIssues as 1 if students mentioned something positive regarding division of labor, −1 if they mentioned something negative and 0 otherwise.

**Transactivity Score.** Each team was assigned a Transactivity score, which was the average of Pairwise Transactivity scores across each pair of students within the team. The team assignment used for this analysis was the final team students worked in for the project.

### 4.2 Online Discussion Quality

The automated team formation paradigm relies on data from the online reflective discussion that was requested of students after each individual project. If the students were not engaged in this process, the paradigm would have broken down from the beginning. One of the big successes we observed was student engagement in these discussions. In total, the students contributed approximately 200 posts to the discussion forum after each individual project. Up through the third individual project when teams recommendations were computed, a total of 1007 posts had been contributed. Out of these, 438 (43.5% altogether) were labeled as transactive in the automated analysis. This suggests that students were engaged in the initial portion of the intervention. Since transactivity is typically low in discussion forums of online courses [25], this finding suggests that uptake of the intervention was strong at the initial stage. The reflection-feedback setup led to substantive discussions between students. Discussion about the methods they used in their individual projects led to fruitful interactions between the students. Even though the teams were co-located and the students were also meeting outside of class, participation in the reflection-feedback setup remained high throughout the course. This was presumably because students found the feedback and interaction they had to be useful. Survey responses highlighted the value of different perspectives, approaches and suggestions that students were able to obtain from their interactions on the reflection-feedback setup. Students also reacted positively to the team suggestions.

### 4.3 Team Formation Processes

As mentioned above, most team recommendations were not taken up in this study. Thus, uptake of the intervention was low at this point. We found that if one team chooses not to take the team recommendation, it has a ripple effect where the students they choose to work with instead must then leave the teams they were assigned, and then their team-mates must also find alternative arrangements. The ripple effect in conjunction with some students desiring to pick their own team meant that the structure overall broke down. In the end, only 5 team recommendations were partially preserved in the teams that were eventually finalized.

The lack of uptake of the recommendations afforded the opportunity to test whether students of their own accord would choose team-mates that inadvertently maximized our estimate of collaboration potential. For this analysis we measured for each student the average Pairwise Transactivity score of the team they were assigned to as well as the average Pairwise Transactivity score of the team they eventually ended up on. The score for teams that were assigned was 1.14, while that of the final teams was .27. The pooled standard deviation was .89. We used a 2-tailed pairwise t-test to test the difference in scores, $t(77) = 7.3$, $p < .0001$ and the effect size was .98 s.d., thus indicating a large effect. For 63.38% of students who did not take the team assignment recommendation, the average transactivity of the self-selected teams was lesser than that of the teams we assigned them to. In 9.86% of the cases, the average transactivity was the greater and in 26.67% of the cases, the transactivity of the assigned and self-selected teams was the same.

### 4.4 Team Work

The final project grade, both the manual and autograded portions, provide an indication of how effectively teams were able to work together. Here the team is the unit of analysis. SelectionProcess is a quasi-experimental variable which we can use to obtain correlational evidence to evaluate the intervention. In this analysis, we investigate the role of Transactivity as an influence on group processes that affect how well teams produce joint work. For both team performance measures, we built an ANOVA model with project grade as the dependent variable, SelectionProcess as the independent variable, and Transactivity score as a covariate nested within the independent variable. We nested Transactivity score because it has different implications for team process if it was used in order to select teams or just happened to be the case. As a covariate, we also included the average grade the students per team scored on an individual assignment they did prior to the teamwork activity. There were no significant effects on the manual portion of the grade, which focused on the written report. However, there was a trend on the autograded portion for the SelectionProcess variable, which targets the actual software they produced, and a significant positive effect of the transactivity variable, $F(4, 7) = 3.3$, $p < .05$. The transactivity variable accounts for an additional 30% of total variance in team performance accounted for by the model. As for SelectionProcess, teams where selection was based on prior friendship performed worse than the other 3 approaches. The two highest scoring categories were Observation of behavior on the platform and Recommendation.

The post-course survey provides an indication of the subjective perception of teamwork within projects. Here the individual is the unit of analysis. In this analysis, we investigate the role of Transactivity as a criterion for team selection as well as implications of student response to the recommendations. We measure perception of teamwork experience using RelationalIssues and DivisionOfLaborIssues as outcome variables. First, we built an ANOVA model with DivisionOfLaborIssues as the dependent variable, SelectionProcess as the independent variable, and Transactivity score as a covariate nested within the independent variable. There was a significant effect of SelectionProcess, $F(3, 69) = 3.4$, $p < .05$. A student-t posthoc analysis indicated that students with SelectionProcess had significantly lower scores than all other students with an effect size of .83 s.d. The TransactivityScore variable showed a moderate positive correlation with DivisionOfLabor issues within the set of students coded as Recommendation suggesting that the recommendations may have been more effective to the extent that the algorithm was able to find a high criterion solution. Next, we built an ANOVA model with RelationalIssues as the dependent variable, SelectionProcess as the independent variable, and Transactivity score as a covariate nested within the independent variable. We nested Transactivity score because it has different implications for team process if it was used in order to select teams or just happened to be the case. In this case, there was no significant effect. However, comparing those students with SelectionProcess coded as Know with all other students showed a marginal negative effect, $F(1, 75) = 1.69$, $p < .1$, effect size of .52 s.d. Overall, this suggests that student tendency to select team-mates they were friends with worked out poorly for them. On the other hand, students who based their choice on their observation of other students' behavior, did not suffer the same fate.

## 5 Discussion and Recommendations

Because the data from this study does not include an experimental manipulation and because it is only a case study from one offering of a single course, no strong claims can be made. However, the case study does illustrate how factors that were not present in the earlier evaluations of the approach impact its success. In this study, the Transactivity-Based matching broke down once some students chose to form their own teams. In order to be successful, the recommendations must be taken by all. However, the fact that the students chose to ignore the recommendations in most cases suggests that forcing students to take a recommendation made without their involvement would not be appreciated by students. However, a policy of recommendations taken by all would not need to require students to be passive recipients of the recommendations. If we can actively engage their preferences in the constraint satisfaction process, we may be able to achieve the success observed in past evaluations of the approach. Consistent with prior work

[18], the data from this study suggests that allowing students to choose to work with their friends is counter-productive. In this course, students appear to be as successful in selection based on goal-directed observation as the algorithm is in transactivity-based assignment. Together these two observations suggest that in engaging the preferences of students in the constraint satisfaction process of team assignment should encourage application of wise criteria observed from behavior within the course rather than selecting friends.

## 6 Conclusions and Future Work

In this paper we have presented a case study evaluating a team assignment intervention that was successful in a 4 week project-based MOOC offered in the past. We described the intervention and how it played out in a 16 week course for credit. The analysis shows some signs of success and many opportunities for growth. In the next iteration of the study, our intention is to inform students up front that a recommendation is coming, engage their observations of behavior in the course in addition to automated observations of Transactive exchange, and use both forms of estimate of collaboration potential in the constraint satisfaction approach.

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