Contrasting Explicit and Implicit Scaffolding for Transactive Exchange in Team Oriented Project Based Learning

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Abstract: Script based support for collaborative learning may employ either explicit or implicit scaffolding. If the effect of script based support is mainly by means of its effect on collaborative processes, it would be reasonable to expect that if two forms of support manipulate the same process variable, they would provide redundant rather than synergistic effects when offered together. However, explicit forms of scaffolding may provide additional benefits from the reification of the processes that they provide, which could be received as instruction. This paper contributes to research on dynamic support for collaborative learning by proposing a novel form of micro-level prompt designed to elevate the amount of Transactive exchange. In a 2×2 factorial design, we measure the impact of this explicit form of scaffolding and an implicit form of support for Transactive exchange developed in prior work, alone and in combination in terms of impact on two key outcomes, namely collaborative product quality and acquisition of multi-perspective knowledge. In this study, the pair of manipulations provide synergistic support for group product quality, but only the explicit support contributes to acquisition of multi-perspective knowledge.

Introduction

Work related to both static and dynamic script based support for collaborative learning has leveraged the theoretical construct of Transactivity (Teasley et al., 2008; Azmitia & Montgomery, 1993;De Lisi & Golbeck, 1999), often demonstrating a mediating or moderating effect on learning, especially conceptual learning of difficult content (Azmitia & Montgomery, 1993; Schellens et al., 2007) and acquisition of argumentative knowledge (Weinberger et al., 2010). In notable recent work, Wen (2016) provides evidence that Transactivity in collaborative discussion can be increased through careful assignment of students to teams based on observation of a past history of Transactive exchange earlier in the course. Building on Wen's prior work, in this paper we address the question of whether explicit scaffolding of collaborative processes provided during collaboration offers an additional beneficial impact on outcomes above that achieved through implicit support. The findings highlight the importance of explicitly reifying desired collaborative processes over elevating those processes through an implicit mechanism such as a team formation protocol.

More specifically, this paper presents a study of dynamic support for collaborative learning at scale as a contribution to the line of research aiming to import research from the CSCL community to the context of Massive Open Online Courses (MOOCs). Interest in collaborative learning in MOOCs has been present since the earliest MOOCs, especially cMOOCs (Yeager et al., 2013). However, the reality remains that participation in typical MOOCs is a solitary experience. The bulk of prior work related to analysis of collaborative or discussion based learning in MOOCs has largely focused on information exchange in discussion forums (Wang et al., 2015; Wang et al., 2016) or designed collaborative learning experiences that are very short activities, such as collaborative reflection activities (Rosé & Ferschke, 2016). While there has been a desire to incorporate more ambitious project-based learning in MOOCs (Ronaghi, 2014), limited success has been reported. Wen (2016) offers hope that this problem can be overcome, by presenting evidence from a combination of controlled experiments and MOOC deployments that demonstrate positive impact of a team formation approach that offers project teams in MOOCs a more productive starting condition. Despite a successful MOOC deployment in which all formed teams turned in a final project, inspection of group processes suggest that additional improvements could be achieved through support of collaborative processes after team formation.

This paper contributes new insights related to dynamic support of at scale collaborative learning, with the goal of providing an empirical foundation for a later high external validity MOOC deployment. The most similar prior work to our own combines high internal validity controlled experimentation in a crowdsourcing environment such as Amazon's Mechanical Turk (Coetzee et al., 2015; Wen et al., 2016) with subsequent high external validity deployments in at scale online learning environments such as online courses or team based MOOCs. In this paper, we present a controlled study that provides design recommendations for a subsequent MOOC deployment that will offer dynamic support of collaborative processes during teamwork in that context.

In the remainder of this paper we first offer an overview of related work leading into the specific hypotheses underlying our study as well as its proposed contributions. Next we offer the details of the design and preparation for our study. Next we offer an empirical analysis of the results of our study. Finally, we discuss what we can conclude from the results and how they motivate the design of a subsequent MOOC deployment.

Novel Dynamic Support Prompts in Relation to Prior Work

Collaborative work can be structured either at the macro level or the micro level. A frequent method for structuring collaborative work at the macro level is the use of what is known as the Jigsaw paradigm (Aronson, 1978), to increase the interdependence between team members. In this paradigm, students are provided with specialized expertise, and the task makes each piece of specialized knowledge that defines the Jigsaw to be necessary in order to achieve a satisfactory collaborative product. The Jigsaw used in Wen et al. (2016) consisted of four bodies of relevant knowledge for a task of constructing an integrated energy plan; each of the four bodies of knowledge focused on the pros and cons associated with one form of energy. Another way to introduce complementarity and interdependence is to assign students to roles that define their intended contribution (Strijbos & Weinberger, 2010; Schellens et al., 2007), such as assignment of different task responsibilities. In our work, we use the same task and Jigsaw paradigm used in Wen's study.

Micro-level structuring focuses more on the collaborative processes themselves. Sometimes this involves reification of desirable forms of contribution to the discussion, such as with scaffolds in a message authoring buffer (Weinberger et al., 2005) or buttons on a structured graphical user interface (Baker & Lund, 1997). Both static and dynamic forms of script based support for collaboration have been evaluated in the prior CSCL literature. A specific form of dynamic support that has been successful at increasing the intensity of substantive exchange of and improvement of reasoning contributions was originally designed as an automated form of what is referred to as Accountable Talk Classroom Facilitation (Michaels et al., 2002). A series of earlier studies of conversational agents employing Accountable Talk Facilitation have been successful at elevating collaborative processes and learning (Adamson et al., 2014). Results from this prior work demonstrate that Accountable Talk based support for collaborative learning significantly increases conceptual learning.

Typically macro and micro level support are treated separately. However, in our work we employ Accountable Talk prompts as micro-level support, but we tailor them to the Jigsaw role of each student. In particular, when we direct a student to evaluate and respond to another student's contribution, we ask them to do so from the perspective of their assigned jigsaw role. Thus, in addition to supporting Transactive exchange, the goal is for the Accountable Talk prompts to intensify the interdependence between students by emphasizing their unique knowledge.

Theoretical Foundation and Hypotheses

A key theoretical construct that underlies our work is that of Transactivity, where our operationalization of Transactivity is defined as the process of building on an idea expressed earlier in a conversation using a reasoning statement. Research has shown that such knowledge integration processes provide opportunities for cognitive conflict to be triggered within group interactions, which may eventually result in cognitive restructuring and learning (De Lisi & Golbeck, 1999). While the value of this general class of processes in the learning sciences has largely been argued from a cognitive perspective, these processes undoubtedly have a social component. From the cognitive perspective, Transactivity has been shown to positively correlate with students' increased learning, since transactive discussion provides opportunities for cognitive conflict to be triggered (Azmitia & Montgomery, 1993;De Lisi & Golbeck, 1999). It has also been shown to result in collaborative knowledge integration (Gweon, 2012), since optimal learning between students occurs when students both respect their own ideas and those of others' (De Lisi & Golbeck, 1999). From the social perspective, Transactivity demonstrates good social dynamics in a group (Teasley et al., 2008).

Wen (2016) showed that by using Transactivity in one context to index collaboration potential in another context, we are able to significantly improve collaborative product quality. This raises the question of whether we can also increase learning with the same implicit support used in that study. However, in the learning sciences, there has often been a tension observed between emphasizing performance and emphasizing learning. In project courses, for example, students tend to take up roles where they can use the knowledge they already have in order to achieve a high quality product, which undercuts the learning that could take place. Often, learning requires focus on skills that are just beyond a person's ability level. Thus, engagement that leads to learning may frequently appear less successful in terms of performance. We cannot assume that a manipulation that supports a high quality product will necessarily support higher learning. In the case of the manipulation of group composition used in Wen (2016), Transactivity played a central role, and as already mentioned much prior work associates Transactivity with learning (Teasley et al., 2008; Azmitia &

Montgomery, 1993;De Lisi & Golbeck, 1999). Thus, ***(1) we hypothesize that the composition manipulation that implicitly supports Transactivity will increase learning.*** Conversely, prior work has demonstrated that dynamic support that intensifies collaborative processes leads to increased learning. Thus, ***(2) we also hypothesize that the dynamic support manipulation of accountable talk that uses an explicit means to increase knowledge integration processes would increase quality of a collaborative product where quality is related to knowledge integration.***

As discussed above, in this study we introduce a novel form of adaptive prompting behavior that aligns the prompts with the students' roles in a Jigsaw task, aiming to elicit more discussion and reasoning related to the unique information the student has. Because such adaptive prompts reinforce the perspectives held by students, ***(3) we hypothesize that the dynamic support we provide that explicitly scaffolds collaborative processes will lead to increased acquisition of multi-perspective knowledge.***

Wen (2016) shows that group composition has a positive effect on group product through moderating Transactivity in collaboration. Because dynamic support using Accountable Talk prompts also aims at increasing Transactivity in collaboration, there's a question of whether the implicit group composition manipulation and the explicit dynamic support manipulation during the collaboration process would interact synergistically or whether they would prove to be redundant forms of support. Prior work suggests that the support for learning offered through scaffolding a structured reasoning process is synergistic rather than redundant with the support received through intensive human interaction when conceptual knowledge is the target of learning (Kumar et al., 2007). Furthermore, explicit scaffolding may be received differently than implicit scaffolding, and thus lead to a different learning effect. ***(4) Thus, we hypothesize a synergistic effect on group product quality if Accountable Talk prompts designed to explicitly scaffold a structured reasoning process are combined with a manipulation designed to intensify collaboration in a more organic implicit way, such as the composition manipulation.***

Method

In order to test hypotheses 1-4, we conduct a 2×2 factorial design where we independently manipulate the presence of the *implicit* group composition manipulation and the *explicit* Accountable Talk manipulation. This enables us to test the impact of the implicit support manipulation and the explicit support manipulation on group product quality as well as testing whether the two manipulations have a synergistic or redundant effect. As a key part of the paradigm for conducting this experiment, we use the same knowledge integration task used in prior research related to the implicit support composition manipulation (Wen, 2016). In order to examine the effects of both factors on individual learning and team product quality, we designed two outcome measures. 1) Individual pre-test and post-test to measure individual learning gains, including both measures of conceptual knowledge and multi-perspective knowledge. 2) A group proposal to measure team knowledge integration quality. The overview of the theoretical model is shown in Fig.1. In the rest of section, we will describe the task we used, the logic of the prompting behaviors in our agent, measurement of learning, participant recruitment and a manipulation check.

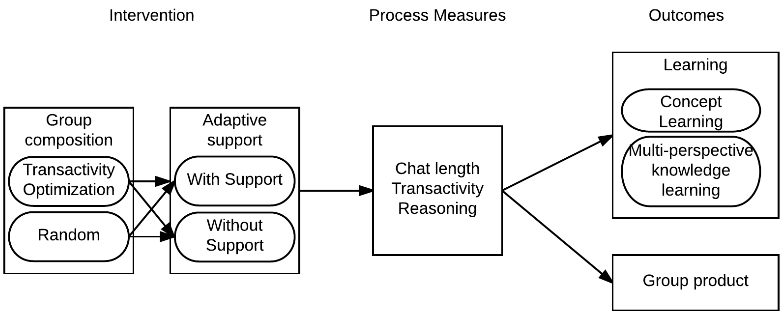

Figure 1. Overview of theoretical model for the study.

Task Description

In order for collaborative learning to be successful, the preconditions for interdependence and substantive exchange and integration should be established. We followed the Jigsaw paradigm and designed this Jigsaw knowledge integration task. Because each student represents a different perspective and receives unique information, it becomes critical for the students to transactively talk to each other and integrate their information to complete the task, which was found to be a successful knowledge integration task (Wen, 2016).

In the experiment, the student works through 6 steps, which take approximately 45 minutes. Step 1 is a pre-test where students are asked to write an individual proposal on an open-ended task involving proposing an energy plan for a city. In Step 2, students read an article. We designed the task to be a Jigsaw task, so that different students read materials focusing on their one assigned energy type, including coal, wind, nuclear or hydroelectric energy as types. In Step 3, students write one individual proposal based on what they have read from their own assigned perspective corresponding to the energy type, including "economical", "environmental friendliness and low startup cost", "carbon neutrality and economy in the long run", "environmental friendliness and reliability". The proposal will be posted to a discussion forum. In Step 4, students comment on each other's proposals. For students in the Transactivity grouping condition that provides implicit support for group processes, they are then assigned to teams of four based on the group formation paradigm developed in Wen et al. (2016) to maximize the observed pairwise Transactivity across all teams, which means team members are assigned based on whom they've had the most Transactive exchanges with in the past, while also enforcing the Jigsaw paradigm. For students in the random grouping condition, they're randomly assigned to teams of four based only on the Jigsaw constraint. In Step 5, students work in teams on a collaborative task using an interface where they write their group proposals on the left, and they will at the same time chat in the chat window on the right. The right window is where we provide the explicit scaffolded adaptive support to them as micro-scripting. Both conditions receive macro-level task structuring in the chat. We will in detail discuss the prompts we provide in the explicit support manipulation in the next section. In Step 6, students do a post-test, which is an isomorphic task to the pre-test with minimal rewording.

Scaffolded Adaptive Scripting

In this section, we give a brief introduction to how the role-aligned adaptive scripting works. We inherited the conversation agent architecture Bazaar from Kumar (2011) and use it to introduce new conversational agent behaviors in this work. The system needs to understand two features from each contribution a student has typed in. The first is whether the student is in support of a plan. We designed this to be key-word based, we keep a dictionary of all possibilities we've found a student has used to refer to a certain plan, such as plan 1, plan A, option A, etc. We also keep a dictionary of all possibilities we've found students using to show being against a plan, such as, "totally against", "don't agree with", etc. We use both rules to decide whether a student is in support of a plan. The second is whether the student shows reasoning. We labeled contributions from our pilot studies as reasoning or not and trained a machine learning model using a machine learning toolbench to assign this label to contributions in our study. At the same time, the system also keeps track of which student has talked least, and which plans have been brought up or fully discussed (i.e., discussed with reasoning).

When the student doesn't show reasoning towards a certain plan, there are two possible prompting behaviors from the agent:

1) Ask the student to elaborate on the plan from his perspective, where there are three templates for this. One example is "Hey xx, can you elaborate on the reason you chose plan # from your perspective of most economical?"

2) Ask the student to compare the plan with another plan that hasn't been fully discussed. For example, "Hey xx, you have proposed plan #, and xx has proposed plan #. What do you think are the pros and cons of the two plans from your perspective of #?"

When the person does show reasoning towards a certain plan, there are two possible prompting behaviors from the agent as well:

1) Ask someone else who has proposed a different plan that hasn't been fully discussed to compare the two plans. "Hey xx, you have proposed plan #, and xx has proposed plan #. Can you compare the two plans from your perspective of #?"

2) Ask someone else to evaluate this plan, for example: "Hey xx, can you evaluate xx's plan from your perspective of #?"

When there's nobody talking for 3 minutes, the agent will pick the person who has talked the least and prompt: "Hey xx, which plan do you prefer from your perspective of xx?"

We went through an iterative design process to keep the amount of support at a reasonable level, and avoid over-scripting. We added additional rules, including 1) One person will not be prompted twice. 2) If a plan has already been fully discussed, it will not be prompted again. 3) The elaboration prompts will wait after having been triggered before being inserted into the conversation. In particular, the agent will only prompt if the student doesn't talk in the next 10 seconds. After adding the constraints, there will be no more than 3 prompts in the 15-minute collaborative task. For most groups, there are 1 or 2 prompts.

In addition to the micro-level adaptive prompts that are only used in the explicit support condition, we also provide a starter prompt and a finishing-up prompt as macro-level support in all conditions.

Measurement of Learning and Group Product

To measure individual learning gains, we administered a pair of identical pre-test and post-test activities. In both cases, it is an open-ended question that asks the student to write an 80-120-word energy proposal for a city based on some basic information we provided about the city. We developed a coding manual to grade the open-ended proposal. Students can learn about energy from all steps in the task, including reading the article, and commenting in the discussion forum. There are two ways students can improve in their ability to articulate a plan from their experience in the collaborative task. In particular, they may learn new pros and cons about an individual energy source, which we consider conceptual knowledge. Or they may acquire new tradeoffs between energy sources, each related to a specific perspective, for example, coal is economical, but hydroelectric support is less so, and nuclear is even less so. We thus introduce two constructs to measure individual learning. 1) concept learning and 2) multi-perspective knowledge learning respectively.

Concept learning refers to learning of correct concept points, such as “coal is very cheap and economical” or “wind is a renewable energy source”. We counted incorrect knowledge points and removed these from the total. Multi-perspective knowledge learning refers to learning of comparisons between different energy types and tradeoffs of one energy type from different perspectives. For example, “nuclear is very reliable for hospitals, whereas wind is very unreliable.” or “Although wind is very environmentally friendly, it can be harmful for bird habitats.” We also took off incorrect comparison/tradeoff points from the total.

To measure group product quality, we graded the team proposals using the same rubric. The inter-rater reliability between two independent coders on a sample of the dataset is Kappa = 0.74. The two coders split up and then coded the remaining pre/post tests and group proposals without knowing which condition they came from. In addition to these outcome measures, we also introduced process measures to measure the quality of the collaboration process. More specifically, we assessed each team’s chat logs, using metrics including 1) number of contributions, 2) number of words, 3) number of reasoning contributions, 4) number of transactive contributions, 5) number of reasoning contributions that are aligned with each member’s assigned role. As mentioned in the scaffolded adaptive scripting section, we trained a machine learning model to automatically predict whether a contribution contains reasoning. We used the same model to compute the number of reasoning contributions in each team’s chat log. Among these labeled logs, we labeled contributions as transactive or not manually. In addition to general reasoning and transactivity, we also looked into how effective our intervention is in eliciting role-aligned reasoning. For example, a student represents coal energy, and he is supposed to argue from the perspective of which energy types are economical; if the student’s contribution either reasons about coal energy, or reasons about other energy types from an economical perspective in a contribution, it is considered as role-aligned reasoning.

Participant Assignment and Manipulation Check

We ran the study on Amazon Mechanical Turk from June to August in 2016. We ran the experiment in batches, with each batch associated with one or the other condition of the implicit group composition manipulation. Thus, each batch is assigned either to the Transactivity maximization condition or the control condition, so that all students within a batch are assigned to a team using the same process. In the rest of the paper, we refer to this manipulation as the Transactivity factor. Within each batch, teams are randomly assigned to an explicit support condition, i.e., either having adaptive scaffolding from Bazaar as micro-scripting in the experimental condition, or no explicit micro-level support in the control condition. In the rest of the paper, we refer to this manipulation as the Bazaar factor. We ran 14 batches in total. Because 3 batches did not end up including at least 16 students, we removed them from our dataset. This is to guarantee that at least two teams are generated in each four of the conditions in each batch. Among the 11 batches, we have 4 batches of random grouping and 7 batches of transactivity grouping. They generated 63 teams in total, the distribution among conditions is displayed in Table 1.

Table 1. Number of teams in each condition

	Group composition: Random	Group composition: Transactivity
Adaptive support: Without Bazaar	14	18
Adaptive support: With Bazaar	13	18

We first did a manipulation check to make sure our grouping assignment manipulation successfully assigned students to groups such that they had a higher history of prior transactive exchange than expected by chance based on the distribution of transactive exchanges in the whole batch. We used one-way ANOVA to compare the average transactivity score during deliberation discussion within groups between those in control condition and those in Transactivity maximization condition and found a significant difference ($F(1, 61) = 8.19$, $p=0.006$), with random assigned groups having a lower transactivity score ($M = 8.56$, $SD = 5.87$) compared to

Transactivity maximization groups (M = 13.28, SD = 6.91). The effect size value computed by Cohen's D is 0.73, suggesting a moderate to high practical significance. We then checked to make sure the random assignment of students across the four conditions was successful in terms of ability to contribute to the task. As a proxy, we evaluated the length of the individual proposal each student wrote prior to the deliberation phase and did not find any systematic difference between conditions. ($F(3, 59) = 1.25$, $p = 0.3$)

Results

The results in correspondence to the hypotheses are summarized in Table 2. As a summary of our results, our finding is that, consistent with prior results of accountable talk prompts on conceptual learning, the *explicit* support intervention increases acquisition of multi-perspective knowledge (as measured by trade-offs). It does not impact collaborative product quality. Conversely, consistent with earlier studies of the *implicit* group composition manipulation, we observe here an impact on collaborative product quality, but not learning. However, an observed interaction effect reveals that the biggest impact on the collaborative product is achieved when both explicit and implicit interventions are combined.

Table 2. Hypotheses testing and results

Hypothesis	Support or not?
(1) The composition manipulation will increase learning, and a key process variable will be transactivity	Not supported
(2) The dynamic support manipulation of accountable talk will increase collaborative product quality.	Partly supported
(3) The dynamic support we provide that scaffolds collaborative processes aligned with students' perspectives will lead to increased acquisition of multi-perspective knowledge	Supported
(4) There is a synergistic effect on group product if accountable talk designed to scaffold a structured reasoning process is combined with a manipulation designed to intensify collaboration in a more organic way, such as the composition manipulation.	Supported

In response to Hypothesis (3), we built an ANCOVA model, using comparison/tradeoff points in post-test as the dependent variable, Transactivity grouping and Bazaar as main effects, and comparison/tradeoff points in the pre-test as a covariate, while also including group ID as a random intercept, to control for the fact that students in the same group may be correlated. We found Bazaar has a significant effect on the learning of multi-perspective knowledge, as represented by comparison/tradeoff points ($F(1, 230) = 5.135$, $p = 0.024$), which is consistent with our Hypothesis (3). The effect size value computed by Cohen's d is 0.30, suggesting a moderate practical significance. In response to Hypotheses (1), we didn't find an effect of Transactivity grouping on either concept learning or multi-perspective knowledge learning. Thus hypothesis (1) is not supported. And there was not an interaction effect between Transactivity and Bazaar on individual learning.

In response to Hypotheses (2) and (4), we evaluated the two factors on the score of group proposals. We first built an ANCOVA model using group proposal score as the dependent variable, Transactivity grouping, Bazaar, and the interaction term as independent variables, as well as the total length of individual proposal of each group as a covariate. We found an interaction effect between the two factors ($F(1, 62) = 5.240$, $p = 0.026$). We then recoded the two main factors Transactivity and Bazaar into one variable indicating 4 conditions. As a planned contrast analysis we compared the group proposal scores across the four conditions. Based on Dunnett t-test, the average score of the condition where both explicit and implicit support were present is significantly higher than the other three conditions (with $p = 0.015$, 0.043 and 0.001 respectively). The other three conditions were not different from one another. This partially supports our Hypothesis (2) that Bazaar is helpful for group product when transactivity is also present. And this confirms our Hypothesis (4) that there is a synergistic effect between the scaffolded adaptive support and the team's composition on group product quality.

In terms of impact on process variables, our finding is that both manipulations influence collaborative processes, but in different ways. In chat logs, Bazaar groups have a marginally higher percentage of reasoning compared to control condition groups. ($F(1, 61) = 3.213$, $p = 0.078$) In addition to general reasoning, we also looked at whether our intervention leads to more role-aligned reasoning, which is a direct result of the intervention. We found for Bazaar groups, students displayed marginally significantly more reasoning behavior consistent with students' assigned Jigsaw roles. ($F(1, 61) = 0.09$, $p = 0.098$) The effect is more salient for students in the random grouping condition. ($F(1, 25) = 4.49$, $p = 0.044$) We don't see a difference on other process measures between the experimental and control conditions. We see that Bazaar increases the concentration in chat, and also increases students' explanation aligned with their perspectives and roles. We also tested whether these process measures had a mediating or moderating effect on outcome measures. Among the process measures, we only see the percentage of role-aligned reasoning has a moderating effect on both group product and multi-perspective knowledge learning.

Discussion

From the above analysis, we found that the explicit adaptive support we provide in the chat is helpful for students' multi-perspective knowledge learning. But the group composition manipulation, which offers implicit support, increases transactivity in the chat, but doesn't show an effect on individual learning. On the other hand, the group composition manipulation has a significant positive effect on group product quality. Thus, in connection with group product quality, we see both manipulations having a synergistic effect. Based on these results, the recommended intervention would depend upon whether acquisition of multi-perspective knowledge or collaborative product quality is the primary target. If multi-perspective knowledge learning is the target, explicit support such as scaffolded accountable talk prompts should be emphasized, which reifies the value of including an integration of perspectives in the discussion. Both manipulations should be used together as they have been observed to work well in tandem for achieving impact on the collaborative product quality.

From the analysis of process measures, we found that the explicit support for transactive exchange encourages students to focus their most sophisticated articulation of domain reasoning in the chat rather than in the collaborative product. The responses to the Bazaar prompts increased the effort required on average per contribution (in particular when students were responding directly to the prompts), which dampened the tendency of the group composition manipulation to increase amount of discussion and integration in the collaborative product. Thus, while the Bazaar prompts improved discussion processes and learning, we do not see this value reflected in the collaborative product quality. On the other hand, it is important to consider that in this task, where effort cannot be simultaneously expended towards the discussion process and the product producing process, a manipulation that intensifies the discussion process may draw attention away from the product producing process. This is true when collaborative discussion and work on collaborative products occurs simultaneously. That is a difference between our setup and many phased collaboration setups in earlier studies. Nevertheless, it reflects the reality of many collaborative setups both in learning contexts and in the workplace. It is possible that if we required a more strict phasing structure, so that discussion occurred strictly before the collaborative work, we could employ both manipulations without any interference or dampening on the learning effect. We leave this for future studies.

Conclusion

In this paper we reported on an experiment to contrast the effect of implicit support through manipulation of group composition and explicit support through providing scaffolded accountable talk prompts during collaboration. This high internal validity investigation motivates subsequent work where we will implement both interventions in future team-based MOOCs, as done with the same study paradigm in earlier work (Wen, 2016). In addition to practical implication for team-based learning in MOOCs, the theoretical contributions of this study are five fold: First, we investigated a novel form of accountable talk prompt that focuses on transactivity from a specific knowledge-based specialization, which was found to be helpful for multi-perspective learning and shows promise to be provided in future project-based courses to reinforce the roles and perspectives of team members. Second, we investigated explicit dynamic collaboration support in the form of accountable talk prompts in connection with a new form of learning (i.e., including multi-perspective knowledge as a learning measure rather than conceptual knowledge alone, which was the target in earlier studies of Accountable Talk prompting). Third, we investigated the generality of the impact of dynamic support in the form of accountable talk prompts to collaborative product quality and found that although the dynamic support is helpful for learning, it wasn't observed to improve collaborative product quality when provided alone. Fourth, we investigated whether the effect of the group composition manipulation demonstrated to be effective for improving collaborative product generalizes to learning. We found although group composition was effective in encouraging team members to chat transactively, it wasn't helpful for either of our learning measures. Finally, we investigated the extent to which the respective effects of the group composition and explicit micro-level scaffolding manipulations, which are assumed to be similar in that they are both grounded in the concept of transactivity, are synergistic or redundant. Consistent with our hypothesis, we found both them to be synergistic.

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