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Authors
Moore, Katherine S.
Corter, James E.

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Can Group Knowledge Diversity be Created On-the-Fly?: Effects of Collaboration Task Design on Performance and Transfer

Katherine S. Moore (kh2122@tc.columbia.edu)
Human Development Department, Teachers College, Columbia University
525 W 120th St., New York, NY 10027

James E. Corter (corter@tc.columbia.edu)
Human Development Department, Teachers College, Columbia University
525 W 120th St., New York, NY 10027

Abstract

Research on human collaboration has suggested that knowledge diversity improves group performance in complex tasks such as design, problem solving and forecasting. However, in educational settings it is important to also ask whether learning and transfer for individuals within the group is enhanced or hindered by diversity in collaborative work groups. We compare performance in a transportation network design task for two types of collaborative groups, and compare their performance to that of individuals. In one group condition (Distributed Knowledge) each dyad member has been trained on a different subtask of a complex joint design problem in advance of the collaborative activity. These different training tasks should predispose the two dyad members to adopt different perspectives, issues, and design strategies, thus generating greater cognitive diversity for the group. In the other group condition (Shared Knowledge) both dyad participants experienced the same training involving both subtasks. Task performance results show a group versus individual advantage in performance, but a non-significant difference in performance between the two group knowledge diversity conditions. The group knowledge manipulation did affect group process, as measured by time spent collaborating, number of turns taken, and number of words spoken. The findings suggest that group diversity can promote individual learning and transfer when sufficient time is allowed for discussion and group work.

Keywords: diversity; network design; collaboration; problem solving; performance; innovation; transfer

Introduction

Previous research has established that groups outperform individuals on a variety of tasks: from retention tasks (Johnson, Maruyama, Johnson, Nelson & Skon, 1981), to measures of academic achievement (Smith, Johnson & Johnson, 1981; Johnson, Johnson, Roy & Zaidman, 1985), to problem solving (Fawcett & Garton, 2005). A growing body of research has shown that groups produce more innovative solutions than individuals (Paulus & Nijstad, 2003). Diverse groups are more likely to develop innovative solutions (Gabbert, Johnson & Johnson, 1986; Page, 2010). Thus, it is understood that relatively diverse collaborative groups have greater potential to discover or design the best solutions.

Group diversity is strongly associated with innovation because diversity provides groups with a variety of differing perspectives ahisnd heuristics (Page, 2007). According to Page, an individual perspective is a solution subset of what is possible. Multiple perspectives occur in a group when individual members possess different sets of ideas of what is possible. Page notes that two people with different perspectives may emphasize different aspects of a problem and conceptualize the same problem differently. The net result is what we will term knowledge diversity, although other differences, e.g. in values, strategies, and communication behavior, might be relevant.

These prior findings suggest that collaborative task design in educational settings should focus on selecting groups with diverse members, diverse specifically in task-relevant knowledge and perspectives. But this is not always possible; sometimes groups already exist, or are formed by self-affiliation, or assessing prior knowledge to manage group diversity is impractical. Thus, it would be helpful to have methods or tasks that can create knowledge diversity in randomly composed or preexisting groups.

An additional consideration arises in educational settings, namely that collaborative activities are often implemented primarily to improve individual learning outcomes, rather than to maximize group task performance. So far, existing research has not fully delineated the relationship between task performance (and the factors that facilitate it) and individual learning (and the factors that promote it). In education settings, many of the positive learning effects of cooperative activities have been reported from studies that implemented task design or other measures to ensure that participants engaged in effective collaboration (Dillenbourg, 2007; Kirschner, Paas, & Kirschner, 2009). Often these collaboration activities are highly structured or scripted (Dillenbourg, 2002; Koller, Fischer, & Hesse, 2006). In contrast, studies using less regulated interactions show varied and, in some cases, negative findings regarding collaborative learning (Gregor & Cuskelly, 1994; Heath, 1998). While groups may be able to consider more possible solutions, and thus develop more innovative solutions, students who have worked in groups are often less able to transfer the relevant knowledge. This finding suggests that collaborative activities that foster group performance may not necessarily maximize individual learning and skill transfer (Kirschner, Paas, & Kirschner, 2009).

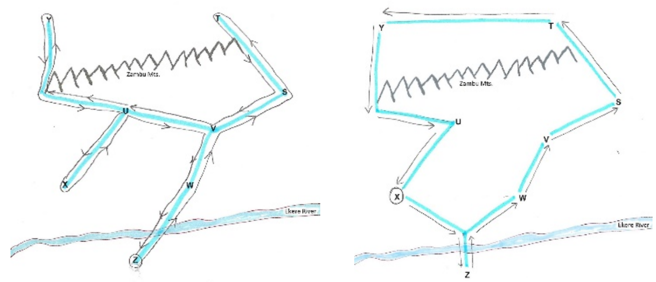
Thus, of particular interest in our research is the question of whether the established benefits of group knowledge diversity are replicated when individual learning is the prioritized outcome measure. What relationship does individual learning have with the knowledge diversity of the group? Are group performance and individual transfer aided or hindered by the collaborative processes evoked by knowledge diversity?

Some relevant data is provided by studies of the jigsaw collaborative learning technique, which was shown to have a positive effect on individual learning (Aronson et al., 1978) and in many subsequent empirical studies (e.g., Chu, 2014; Oakes et al., 2019) with some exceptions (Souvignier & Kronenberger, 2007). As with our knowledge diversity manipulation, the jigsaw creates a diverse- or complementary-knowledge condition (Johansson et al., 2005; Nokes-Malach et al., 2015), in which partners have knowledge or expertise that can contribute different components of a solution that the group needs. However, the jigsaw is cumbersome in that it requires an individual's participation in multiple groups, meeting sequentially, to establish knowledge diversity within the final work group. We are interested in determining if similar knowledge diversity can be achieved while simplifying the jigsaw manipulation, using differentiated individual training tasks as a kind of macro-script (Dillenburg, 2007) to optimize the collaborative work group experience.

Thus, our first aim was to determine if we could generate different skills, knowledge, and perspectives across the two dyad members with a differentiated training-task manipulation designed to enhance knowledge and perspective differences in groups, effectively "engineering" better knowledge diversity in a dyad. These diverse-knowledge dyads are hypothesized to perform better than homogenous-knowledge dyads. Our main goal was to determine whether these two group conditions lead to improvements over the individual condition and whether the knowledge diversity manipulation improves group performance, collaboration process, and individual learning / transfer for the diverse-knowledge groups.

Empirical Study

Our investigation was conducted in the context of a collaborative design optimization task, dubbed the "Relief Aid" game. This "game" is based on two simultaneous network design problems. One network design problem participants faced is commonly referred to as the traveling salesman problem. The problem is to design the shortest route among a set of points on a map. The route must follow a path that visits all points exactly once, returning to the starting point. This task suited our purposes because it permits a variety of possible solutions, affords space for diverse perspectives, and allows multiple design strategies.



1A 1B

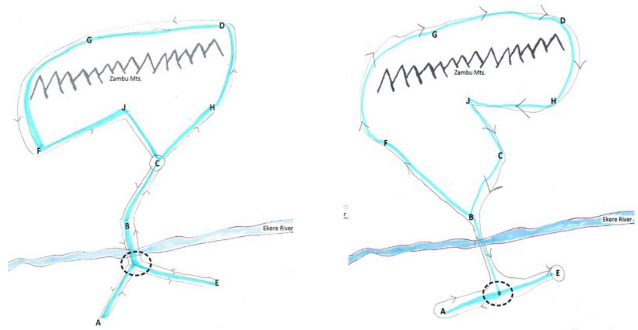
Figure 1: Two example solutions for the joint problem of designing the minimal road network (indicated using a blue marker) and route networks (directional route indicated by arrows, in pencil) on a map in the plane. Panel A presents a solution that does a good job of minimizing the road network length. Panel B depicts a solution that achieves a relatively short route network by reducing the retracing of arcs, but at the expense of (minimizing) road network length.

A layer of complexity was added to the basic traveling salesman problem by imposing the additional task of designing a minimal-length road network upon which the delivery route must travel. This subtask, in isolation, corresponds to another formal problem in network theory, the problem of finding the minimal Steiner tree connecting a set of points. Thus, the task involved two distinct subtasks: attempting to design a minimal-length road network and a minimal route or tour using this same road network (see Figure 1). These two subtasks can work at cross-purposes, therefore simultaneously trying to optimize (minimize) the length of the road network and the length of the tour route is challenging, and can present interesting (or frustrating) trade-offs and potentially cause controversy between group members. In essence, short road networks make the tour routes less efficient and short route networks often require lengthening the road networks underneath them.

Method

To address our research questions, we randomly assigned participants (n = 104) to one of three conditions: Dyadic Distributed Knowledge (induced by varying training tasks) (DDK condition), Dyadic Shared Knowledge (induced by common training tasks) (DSK condition), or Individual work (IND). Participants in the Individual condition worked as individuals on the joint design problem, simultaneously designing the shortest road network and the shortest tour, for two maps: a pre-task or training task and a main (criterion) collaborative task. In the Dyadic Shared

Knowledge (DSK) condition, participants worked as individuals to complete the joint design task on the training task, and in dyads for the main task. In the Dyadic Distributed Knowledge (DDK) condition, participants worked as dyads for the main task; but the two individuals experiences different training-task instructions and subtasks:



2A 2B

Figure 2: Sample participant solutions for the main collaborative task. Both figures show examples of solutions that used both a loop and a Steiner point. The Steiner point is circled with a dotted line in each example.

one participant was tasked with constructing the shortest road network (only), and the other individual was tasked with constructing the shortest tour or route connecting the points (only). Thus, when participants in the Dyadic Distributed Knowledge condition came together as a dyad to work on the main collaborative task, their differing prior experiences presumably created different perspectives on the joint task.

The progression of tasks began with the pre-task, followed by the criterion task, and concluded with a post-task questionnaire. The pre-task was always completed individually, then followed by the main criterion task, which was completed collaboratively or individually depending on the condition. After the dyad (or individual) completed the criterion task, all participants completed a questionnaire with specific transfer questions that prompted them to apply certain key design insights or innovations. Here, we use transfer as our measure of individual learning because it suits the study design. Transfer learning occurs when knowledge or insights gained while solving a problem are successfully applied to a different but related problem in the post-task.

In pilot studies, we had identified two design features, Steiner points and loops, as potential innovations to be discovered by participants that usually improve the network design by shortening total network length. A Steiner point, identified and discussed by Jakob Steiner in 1826, is an added node in a graph, which shortens one or more paths. Using a Steiner point on the present task essentially creates a new "road intersection" not located at one of the "villages" on the map. Depending on its placement, this added intersection enables shorter road or route networks (Figure 2). The second type of innovation we have identified is the use of loops. Loops often enable shorter routes or tours, though they cannot occur in a minimal road network. The loop innovation permits routes to avoid traveling back along previously traveled roads; thus using a loop can result in a much shorter tour (Figure 2).

Criterion task performance was determined using the proposed network solution for the main task. The objective performance criterion (to be minimized) was the total summed length of both the road and the route networks (measured in cm, using Adobe Illustrator SC3 Line and Measure tools). We also coded use of the two target inventions or insights (use of a Steiner point and/or a loop) on the training task, main task, and post-task questionnaire. Individual learning and transfer of innovations was inferred using questions from the post-task questionnaire. If a participant used a loop or Steiner point in answering the relevant post-test questions, it was counted as a successful transfer of learning. Thus we were able to compare the three conditions as to task performance and transfer of innovations.

Note that the map design task is essentially a discovery learning activity. During the pre-task, participants may discover the key design features and generate an optimal solution, but they may not. No feedback or guidance, beyond the rules of the task, were given to participants, neither during the training nor during the main criterion task. Thus, this task differs from highly scripted collaborative learning activities in which participants follow a structured or scaffolded script to guide their interactions. Instead, our collaborative task may best be described as a macro-script (Dillenbourg & Tchounikine, 2007); here, collaborative communication processes, such as negotiation and argumentation, may occur as a result of the task design, but it is not guaranteed.

Results

The results show, first, that we were successful in our efforts to "engineer" varying experience and perspectives via variants of the training task. Individuals (in the Dyadic Distributed Knowledge condition) whose training task had asked them to design routes used the loop innovation with greater frequency on the training task than participants who were not predisposed to it by their training task (road designers): $\chi2(1, N = 38) = 13.328$, $p < .001$. This suggests that route designers found the *loop* a valuable addition to their network design, while road designers did not, meaning that our manipulation of participant prior experience to create differing perspectives regarding these useful design insights was at least partially successful. However, there was not a significant difference in the use of the Steiner point insight between road and route designers on the training task, $\chi2(1, N = 38) = .991$, $p < .319$.

In general, dyads outperformed individuals in the criterion task. As shown in Table 1, dyads of both types, Dyadic Distributed Knowledge (DDK) and Dyadic Shard Knowledge (DSK), created designs with shorter total network length (M=135.73 versus M=140.96), $t(64) = 5.226$, $p = .015$, $d = .642$. This difference in total distance seems to be due to the fact that dyads designed shorter route networks than individuals (M=74.62 cm versus M=81.36 cm), $t(64) = 6.739$, $p = .013$, $d = .624$.

Qualitatively, dyads tended to use different road network designs than individuals. Road networks designed by individuals tended to use a tree or lattice network (as in Figure 1A), which often result in relatively long travel routes because of the need to trace and retrace each branch. Dyads tended to design networks that minimized route length by minimizing the amount of re-tracing needed, accomplished by including loops and Steiner points in their road network designs, as in Figure 1B.

Table 1: Mean distance (cm) of road, route, and total network for the main task group work, by condition (SD shown in parentheses).

Condition	N	Road	Route	Total
Individual (IND)	27	59.60	81.36	140.96
Dyad: Shared (DSK)	19	61.32	74.32	135.63
Dyad: Distributed (DDK)	19	60.90	74.93	135.83
Total	65	60.48	77.42	137.90

Figure 3 presents a box-and-whiskers plot of the distribution of total network length by condition. This plot shows that differences among the conditions in mean network length arise largely because very poor performance is relatively rare in dyads. Participants in the individual condition (IND) submitted designs with a wide range of network lengths, while dyads submitted designs with a distribution of total network lengths that is more uniform (the interquartile range is much more compact). However, five outlying dyads did not seem to show benefits of collaborative learning; these are case numbers 191, 182, 116, 107, and 110. In addition, two outlying dyads performed *better* than the typical dyad in the Dyadic Distributed Knowledge condition. These are case numbers 134 and 152 in Figure 3.

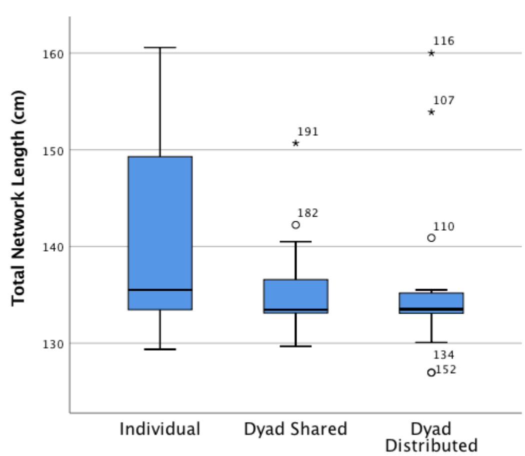


Figure 3: Total network distance by experimental condition (error bars = 95% CI).

Is there any aspect of *group process* that can explain why groups tend to perform better than individuals (or less often perform badly)? To investigate this question, we analyzed group process variables measured from the dyadic conversations. Table 2 presents descriptive summaries of several group process variables, including the amount of time spent collaborating (Collaboration), the number of words spoken (Words Spoken) and turns taken (Turns Taken) during the collaborative group work. In order to identify process variables that may be associated with high or low performance, this table compares aggregate group process variables from low performing outlier dyads and high performing outlier dyads (as defined by the box-and-whiskers plots of Figure 3) to the mean group performance of the lumped Dyadic Distributed Knowledge (DSK) and Dyadic Shard Knowledge (DSK) conditions.

Table 2: Means of group process variables used during the collaborative task (Map 2) for poor and high performing outlier groups, compared to the overall group condition means for DSK and DDK (N=104).

Process Variables	Poor Perf. Outliers	DSK	DDK	High Perf. Outliers
Road Network Length (*cm*)	58	59	61	55
Route Network Length (*cm*)	94	75	75	72
Total Network Length (*cm*)	151	134	136	127
Collaboration Time (*min*)	7	11	11	12
Number of Turns Taken	93	91	90	164
Number of Words Spoken	631	643	699	1222
Freq. of Steiner Point	0%	35%	40%	100%
Freq. of Loop	50%	75%	65%	100%

Table 2 offers several hints as to possible reasons why groups tend to outperform individuals. First, use of key insights, such as the loop or the Steiner point, seems especially common among high performing outliers. Second, high performing dyads talked almost twice as much as low performing dyads (as measured by mean number of turns taken and number of words spoken). This suggests that the more a group engages in discussion, the more likely they are to develop insights that can improve their solution.

We then proceeded to inferential tests of whether our knowledge diversity manipulation affected group (dyad) performance on the main criterion task; essentially seeking to determine whether the knowledge diversity manipulation positively impacted the outcome variables. The three analyzed performance variables were road network distance, route network distance, and their sum, i.e., total network distance. We found no significant differences for these criterion variables: dyads whose members were predisposed by the training task to differing perspectives (the Dyadic

Distributed Knowledge condition), did not develop better (or worse) network design solutions than dyads predisposed to shared perspectives (Dyadic Shared Knowledge): road network, *t*(36) = .281, *p* = .780; route, *t*(36) = -.233, *p* = .817; total network, *t*(36) = .929, *p* = .929.

We also found that the two dyadic conditions (DDK and DSK) do not significantly differ in measures of group process (Table 2): Collaboration Time, t(36) = .086, p = .932, Number of Turns Taken, t(37) = .077, p = .939, Number of Words Spoken, t(37) = -.574, p = .569. Overall, dyads tended to discuss the problem using relatively the same amount of time with the same amount of conversation, regardless of their knowledge diversity condition.

Finally, the knowledge diversity manipulation did not have a significant effect on learning and transfer. Participants in the Dyadic Distributed Knowledge condition transferred insights to the post-task questionnaire with about the same frequency as participants in the Dyadic Shared Knowledge condition: for loops, $\chi2$(1, N = 78) = .412, p = .521; for Steiner points, $\chi2$(1, N = 78) = .412, p = .521. Additionally, dyads did not show greater transfer than individuals: loop, $\chi2$(1, N = 104) = 1.902, p = .168, Steiner point, $\chi2$(1, N = 104) = .004, p = .950. This finding supports doubts raised by Gregor and Cuskelly (1994), and Heath (1998), suggesting that collaborative group work may not benefit individual learning and transfer, even when it improves task performance. Our findings suggest that even knowledge diversity of the group may not help boost learning and transfer for individual group members.

Returning to the collaboration process variables presented in Table 2, we asked if any of these process variables were correlated with criterion task performance. We found that several were. Table 3 displays these relationships. There is a significant negative relationship between the amount of time a dyad spends collaborating during the main task (Collaboration) and the length of their route, R2 = -.333, p = .041, as well as the length of their total network, R2 = -.337, p = .038. As dyads spend more time collaborating, the length of the route and total network decrease, indicating better performance on the criterion task.

In contrast, the length of the road network was significantly and positively correlated with the number of turns taken, R2 = .358, p < .001, and the number of words spoken, R2 = .260, p = .011, but not with collaboration time, R2 = .097, p = .563. This seems to indicate that more dyadic conversation was associated with worse performance in minimizing road length. However, note that road length and route length are negatively correlated, indicating the tradeoffs required in this dual-network design task. Thus, more conversation tended to result in shorter routes and total network length, but this optimization seems to have required some lengthening of the road network (perhaps to enable routes incorporating loops).

Table 3: Correlations between group process variables and criterion performance variables. Lower values of the criterion variables (4-6) indicate better performance.

	Group Process		Criterion Performance		
	2.	3.	4.	5.	6.
1. Collaboration	.59**	.64**	.10	-.33*	-.34*
2. Turns Taken	--	.78**	.36**	.04	.14
3. Words Spoken		--	.26*	.04	.13
4. Road Length			--	-.48**	.08
5. Route Length				--	.84**
6. Total Length					--

** p<.011 (2-tailed) * p<.05 (2-tailed)

Regarding the relationship between group process and individual learning and transfer, we found no significant difference in collaborative processes between participants who transferred the loop insight to their post-task questionnaire and those who did not: Collaboration Time, t(74) = -1.466, p = .147, Number of Turns Taken, t(76) = -1.344, p = .183, or Number of Words Spoken, t(76) = -.871, p = .386. Nor were there significant differences for Steiner point use: Collaboration Time, t(74) = -.561, p = .577, Number of Turns Taken, t(76) = -.039, p = .969, or Number of Words Spoken, t(76) = -.601, p = .550.

However, when we filtered the data to examine only participants who successfully transferred the Steiner point insight, in order to identify what collaborative processes these successful learners used, we found a significant difference between the Dyadic Distributed Knowledge and Dyadic Shared Knowledge conditions in the number of words spoken during the collaborative process (DSK μ = 403, DK μ = 633), t(26) = -2.820, p = .009, *d* = 1.087 (Table 4). We found a similar relationship regarding number of turns taken, (DSK μ = 59, DK μ = 76), t(21.558) = -1.869, p = .075, *d* = .670, approaching significance with equal variances not assumed. This suggests that individual group members who successfully transfer this insight tend to show a greater amount of communication (more words exchanged and possibly more turn taking) in groups with distributed knowledge compared to groups with shared perspectives. We conclude that conditions of knowledge diversity may require more communication than homogeneous knowledge in order to achieve successful transfer.

Table 4: Dyadic task process variables for individuals who successfully transferred valuable insights.

	Group Process Variables		
Transfer of Loop	Collab. (min)	Turns Taken	Words Spoken
Dyad: Shared (DSK)	11.13	74	502
Dyad: Distributed (DDK)	11.37	67	539
Total	11.25	71	519
Transfer of Steiner Point			
Dyad: Shared (DSK)	10.41	59	403
Dyad: Distributed (DDK)	11.72	76	633
Total	11.14	68†	526**

†.05<*p*<.10 (2-tailed), **p*<.05 (2-tailed), **p<.01 (2-tailed)

Conclusions

We found that groups outperform individuals in the network design task, adding to the literature showing performance advantages for collaborative groups in various STEM tasks.

We have also demonstrated that it is possible to "engineer" dyad knowledge diversity via task design, using a short training task to promote different predispositions in team members to particular insights on a problem-solving task. Yet, our two knowledge diversity conditions (DDK and DSK) did not significantly differ in the group task performance nor in individual learning and transfer.

However, engineered knowledge diversity did seem to impact the group collaborative process. First, we established that group performance on the criterion task benefits from more collaboration; there was a negative correlation between collaboration time and total network length (the criterion was to be minimized). When we examined collaborative indicators by participants who did successfully demonstrate transfer, we found that those in the knowledge diversity condition (DDK) tended to communicate significantly more than participants with shared common knowledge (DSK). This suggests that diverse groups, with members who are predisposed to different perspectives, may need more communication time in order to understand and learn, as compared to groups whose members have similar perspectives.

Regarding learning, the results suggest that successful transfer may be mediated by different group processes depending on the diversity of prior experience of the group. Homogeneous-knowledge groups, whose members share prior knowledge and perspectives, seem able to transfer insights when the collaborative process is relatively short, defined by fewer words and fewer turns taken. However, groups with diverse knowledge are best able to transfer insights when the collaborative process involves more discussion and more turn taking. It may be that as regards learning and transfer, knowledge diversity in groups is a "desirable difficulty" (Bjork, 1994). Transfer may be influenced by the conversations, shared opinions, or arguments that arise as a result of the diverse or shared perspectives of group members. Further research is needed to more deeply examine the effects of communication processes on learning in collaborative work.

Discussion

Groups that discuss and selectively process information have shown accelerated learning in many studies, and may be more likely to find useful abstractions (Schwartz, 1995). The participants in our study who successfully transferred design insights seemingly benefited by engaging in more extensive dialogue. Indeed, the process of explaining one's knowledge to one's partner may have benefited both members of the dyad, since generating explanations has been shown to positively impact learning (Webb et al. 1995) and receiving information may trigger selective information processing, which has also been shown to positively affect learning (Voiklis & Corter, 2012). It is a truism that a need for communication is created by asymmetries of information. Our knowledge diversity manipulation is one way of introducing asymmetrical experiences, thus presumably motivating more extensive dialogue between partners, which can in some case have a positive effect on learning and transfer.

Our results are consistent with two cognitive and social models of collaborative learning: namely, complementary knowledge (Johansson et al., 2005; Nokes-Malach et al., 2015) and collaborative controversy (Smith, Johnson, & Johnson, 1981). Complementary knowledge is a cognitive mechanism that is engaged when partners have knowledge or expertise that may contribute different components of the solution. This is essentially a parallel processing model of cognition, in which needed information is distributed among the group so as to avoid burdening any one member with cognitive overload. Instead of attempting to understand all relevant information, one partner can simply ask the other partner (e.g., the "expert") instead of attempting to internalize the information. Because the information is distributed, communication is essential to fully processing and understanding and solving the problem.

Our knowledge diversity manipulation created an opportunity for complementary knowledge by distributing the information needed to perform well in the criterion task among the members of a dyad. In such situations, communication processes may serve as critical links allowing the group access to distributed information. For this reason, it makes sense that we found that communication processes play a more important role among dyads with distributed knowledge (i.e. complementary knowledge) who successfully transfer information, as compared to dyads with shared (not distributed) knowledge. Shared knowledge does not create an opportunity for complementary knowledge and thus a lesser need for communication (as all group members are in possession of all relevant information and do not need to seek it from others). Our finding that the shared knowledge diversity condition promoted less communication supports this understanding.

The present findings may also relate to controversy in collaborative groups, which has been shown to promote higher retention and more accurate understanding of multiple perspectives as compared to collaborative groups that avoid controversy (Smith, Johnson & Johnson, 1981). Controversy exists in a dyad when one partner's ideas, information, or perspectives are incompatible with those of their partner, and the two seek to reach an agreement (Johnson & Johnson, 1979). In situations such as these, the negotiations necessary to reach agreement are only possible through communication. Thus, it is the shared goal of determining a shared solution that motivates dialogue despite controversial perspectives.

Our knowledge diversity manipulation not only introduced differing perspectives, it introduced perspectives that were at odds with each other; each participant entered the collaborative activity with the goal of combining their prior-experiences, yet their prior-experiences involved conflicting strategies. This introduced a degree of controversy, essentially creating situations in which negotiation and compromise were needed for partners to settle on a final solution. Yet, participants in our controversy laden condition did not outperform or transfer learning to a greater degree than participants who collaborated without this kind of controversy. While this null finding does not support the Smith et al. (1981) results, it is important to note that the collaborative processes of our two conditions significantly differed. Participants more likely to experience controversy as a result of our manipulation communicated to a greater degree than those who were less likely to experience controversy, because it was not induced. This suggests that emphasizing independent or conflicting goals to different group members, may facilitate learning and transfer, but only when mediated by collaborative communication. Situations where this additional time is not available may even lead to process loss, cases where collaboration leads to worse performance, learning, and transfer than individual work (Kerr & Tindale, 2004).

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