Title
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Learning Through Collaboration: Designing Collaborative Activities to Promote Individual Learning

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Abstract

Knowledge diversity is widely acknowledged to be beneficial for collaborative groups engaged in problem solving. An experiment was conducted to determine whether knowledge diversity and assigned task roles for members in an online virtual collaborative group affect group task performance and individual learning and transfer, and to explore the role of explanations as a mediating variable in these effects. Two control conditions were included that involved individual work, with and without self-explanations. Results showed that the frequency of explanations in dyadic discourse were correlated with individual learning, and that groups with knowledge diversity tend to use more explanations. These findings suggest that discussing explanations is a key feature of successful group work that contributes to determining how much individual learning occurs and how well it transfers from collaborative activities to similar, novel tasks.

Keywords: collaborative problem-solving, cooperative learning, explanation, elaboration, self-explanation, group diversity, network design.

Introduction

Peer collaboration has been identified as an effective educational approach to promote learning and discovery (e.g., Johnson & Johnson, 1999; Barron, 2003), exchange of original insights and critical thinking (Bos, 1937), resolution of differing perspectives through argumentation (Amigues, 1988), observations of alternative strategies (Azmitia, 1988), attention to explanations (Webb, 1985), greater transfer of learning (Brandon & Hollingshead, 1999), and social skills such as communication, presentation, problem-solving, leadership, delegation and organization (Cheng & Warren 2000). Recently, collaboration has been identified as a critical 21st-century skill for workplace success (Rios et al., 2020).

For these reasons, collaborative group work has become an increasingly common instructional practice in K-12 classrooms, particularly those implementing STEM curricula, e.g., the Next Generation Science Standards (NGSS), and Project Based Learning (PBL). School districts, state departments of education, national research organizations, and curriculum specialists in the U.S. recommend (or even mandate) the use of peer-based learning (California State Department of Education, 1985, 1992; National Council of Teachers of Mathematics, 1989, 1991; National Research Council, 1989, 1995).

What makes collaboration such an effective learning method? Prior evidence amply documents that groups tend to perform and innovate better than individuals. One possibility is that groups with knowledge diversity – a difference in perspectives or heuristics among group members that promotes different strategies and innovations during collaborative group work – may have some advantages over less diverse groups and certainly over individuals (Moore & Corter, 2020).

However, some established techniques for promoting diversity of knowledge and perspectives in cooperative group work (e.g., the Jigsaw) also involve assigning different group members *to different social or task-related roles,* for example asking one student to act as Recorder for the group or asking different students to become "experts" in different aspects of the collaborative task. To clarify the resulting confound, the current study attempts to separate the effects of the cognitive manipulation (i.e., a training task that uses different subtasks to distribute experience of different solutions or insights among group members) from the social manipulation (explicit assignment of nominal roles to distribute social responsibilities among group members).

A second research goal is to test for mediating effects of cognitive elaboration, a mental sense-making activity that is presumed to occur automatically due to the cognitive demands of dialogue, especially as one *explains* one's memories, actions or thinking aloud to another person. In an attempt to isolate the effects of this factor from other social and cognitive effects of group work, the study design adds a similar elaboration component (i.e., self-dialogue, also called "self-explanation") in one individual-work condition. In this condition, participants are prompted to explain their thinking aloud while working solo.

Method

This research study is designed to distinguish between the effects of two aspects of collaborative activities on group process, group performance, and on individual learning and transfer. These two aspects are knowledge diversity (induced by varying experiences with a pre-task as a training task) and assigned task roles (induced through the task during of the dyadic tasks). Group process is assessed by coding and analysis of the group discourse, in terms of a number of speech acts relevant to collaboration. In particular, we are

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interested in the effects of *explanations* on learning and transfer, both in the group discourse and self-explanations by individuals in one of the control conditions.

Study Design

The research questions are addressed using a two-by-two factorial design with two added control conditions. The four main conditions are Diverse Knowledge with and without Roles, Shared Knowledge with and without Roles, and the control conditions are Individual work with Self-Explanation and Individual work *without* Self-Explanation. As in the pilot study, the experimental procedure involves three stages: a pre-task, a main task, and a post-task questionnaire.

Diversity conditions are introduced using the pre-task as a short training task in which the two members of a dyad in the Diverse Knowledge conditions (with or without assigned task roles) receive task directions that introduce them to different sub-tasks or components of the main problem-solving task. Because performance on each sub-task benefits from a strategy that is also beneficial in the main task, the different training tasks introduce dyad members to equally valuable, but different perspectives on how to solve the problem in the main task. In the Shared Knowledge conditions (with or without roles), the two members of the dyad receive the same task directions in both the pre- and the main problem-solving tasks. Thus, they have the same training experience when they arrive to collaboratively solve the main task.

The assigned task role manipulation was introduced in the directions of the main problem-solving task. Dyads in the assigned-task-roles condition were informed that they and their partner had experienced different problem-solving tasks during the pre-task, and instructed that one person should act as the "road builder" consistent with their prior experience and the other should act as the "route planner" (see The Collaborative Task, below for details on these roles). Dyads in the condition without assigned task roles were informed that they and their partner had experienced the same problem-solving task during the pre-task, and thus have similar experiences.

The study design uses two control conditions in which participants complete the pre- and main problem-solving tasks without a partner; thus, controlling for the social effects of communication between the two members of the dyad on any performance or learning outcomes. Participants in these two control conditions, first work alone on the pre-task. Then, they are given a new different map as the main task, in which they (again) work alone.

Afterwards, participants work individually to complete a post-task questionnaire designed to assess transfer learning. All work on the main task was video recorded, transcribed, and coded to identify nine speech acts associated with collaborative learning activity, including explanations.

The Collaborative Task

The design optimization problem faced by participants in the present study involved two distinct subtasks: attempting to design (a) a minimal-length road network connecting a set of points and (b) a minimal-length route or tour using this same road network. 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. These tradeoffs arise because of a basic conflict regarding the network design: 1) short road networks make the tour routes less efficient because they require the truck traveling the route to re-trace each edge of the network and 2) short route networks often require lengthening the road networks underneath them in order to complete a loop, often a key feature of efficient tours. This potential conflict may motivate negotiation, explanation, and argumentation. This affords the current study the opportunity to examine the effects of these communication behaviors on performance and learning.

Here, the problem solver is asked to imagine that relief aid supplies must be delivered to a set of remote villages and confronted with a map with the location of ten villages plotted. The participant is asked to minimize costs by designing the shortest possible road network to connect the points (in general this would be a minimal tree graph), while simultaneously designing a minimal length tour on all the points (described as the route a supply truck will have to drive using the road network). The route must follow a path that visits all points exactly once, returning to the starting point. The mountains (see Figure 1a and 1b) introduce a non-Euclidean constraint: that the route must travel around (not through) this feature. The river – in combination with an explicit rule limiting river crossing to a single bridge – introduces another constraint, creating a bottleneck through which the network must pass.

Participants attempted two examples of this design problem. Working on Map 1 was the training task; this was always done individually. Working on Map 2 was the main or criterion task; this was done either in a dyadic condition or in an individual-work condition. During the main task (Map 2), dyads collaborated to design the road and the route networks, while individuals worked alone.

In this optimization task, with its inherent tradeoff or conflict between the road and the route subtasks, two design features can be helpful: the Steiner point and the loop. Briefly, a Steiner point is an added node in a graph, which shortens one or more paths. A loop is a path that connects a set of points on the map and returns to the start. When used together, these design insights significantly shorten the length of the total network.

Because the study is designed to examine whether (and how) insights gleaned during collaborative group work are transferred, participants are not explicitly instructed about these insights. If a participant had the insight to use a Steiner point or a loop, it emerged through discovery learning.

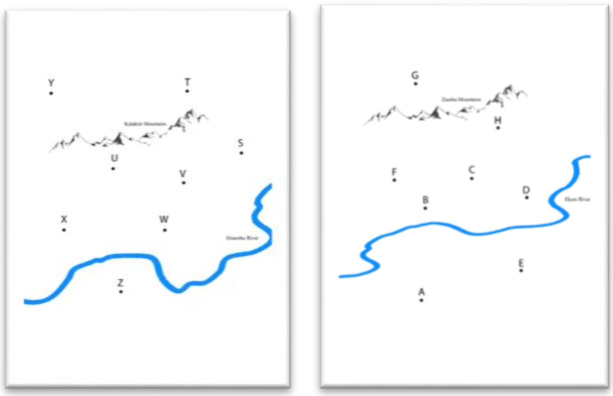

Figure 1: The first map (Map 1) given to participants as a training task (LEFT). The second map (Map 2) given to participants as a collaborative task or as another individual task, depending on assigned condition

Criterion Variables

The research questions and study design focus on three outcome variables: task performance, transfer learning, and communication or speech acts (with specific interest in explanations). This section operationalizes each variable.

Task Performance Criterion task performance was measured using the Map 2 dual-network solution, Road network length + Route network length = Total network length. The objective performance criterion (to be minimized) is the total summed length of both the road and the route networks.

Transfer Learning Learning was measured as the frequency of transfer of two network design features to a set of individual post-task activities. This sub-section includes operationalizations of the terms (a) frequency of transfer, (b) design features, and (c) the post-task activities, beginning with the later and ending with the former.

The post-task activities, used to measure the transfer of network design features, were completed after the first two network design tasks (Map 1 the pre-task or training task and Map 2 the main task which was collaborative for dyads). Each post-task required a network design solution similar to those experienced in Map 1 and Map 2. Tasks were designed to benefit from (be minimized by) either one or both of the design features: Steiner points and loops. This allowed for the identification of incorrect transfer or transfer error. The design features are briefly described below.

Design Insights 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 "Relief Aid" task requires creating a new "intersection" node, not located at one of the villages on the map, from which roads could radiate or connect. Depending on its placement, this innovation enables shorter road or route networks.

A loop is a path that circles through a set of points on the map, connecting all the points and returning to the start; in graph-theoretic terms, it is a cycle. The benefit of the loop innovation in this task is that it minimizes backtracking, shortening the route length, thus the total distance of the network. Loops often enable shorter routes or tours, although a loop cannot occur in a minimal road network, which must be a tree, i.e., a connected graph without cycles.

The criterion for successful learning and transfer of these design insights was the frequency with which participants applied these design features to the novel network design problems in their post-task activities. Transfer learning is the adoption of learning in one context followed by the application of that learning in another context (Woodworth & Thorndike, 1901; Ellis, 1965). Each of the five post-task activities are considered near transfer activities because (a) participants completed them immediately after the first and second network design activities and (b) the post-task activities benefit from network design knowledge and skills that are identical to those from the main task.

Communication Communication was measured using automatically generated transcripts of the study sessions. Zoom automatically time stamps and transcribes the audio file. This process automatically parses transcripts into utterances by speaker turn taking. Each turn is a segment of speaker-continuous speech. Transcripts were then human coded to identify specific types of utterances or meaningful phrases, referred to here as "speech acts." A summary of the coding scheme for speech acts is described in Table 1.

Table 1: Summary description of speech acts.

Speech Act	Description
Explanation (E)	Expresses consideration of an idea, response to describe an action, a thought, state the rules, or prior knowledge
Propose (P)	Suggest a task-related action
Question for Consideration (Qc)	Request consideration or feedback on an idea
Question for Information (Qr)	A question to solicit information or clarification
Response Agree (Ra)	A response to any type of previous statement that expresses agreement
Response Modify (Rm)	A response to any type of previous statement that suggests modifications
Coordination of Joint Attention (J)	Any utterance meant to direct a partner's attention.
Social Facilitation (S)	An attempt to address, manage, or grow a social relationship
Interruption (I)	Any utterance that interrupts the previous speaker

Participants

Participants were recruited from an all-women's college in Northeastern United States, and received course credit for participation. Participants (N=273) were 19.39 years of age on average (range, 18-45 years), and were majority English speaking (69.2%) females (89.9%) who had not yet earned their undergraduate degree (98.9%).

Procedure

Participants arrived at each study session by way of a Zoom link. In the meeting, each participant received a private message through the Zoom chat with a link to a second two-minute video in which the task directions were displayed and read aloud. Private messages allowed participants to receive different, condition specific task directions, which facilitated the distributed knowledge experimental manipulations using differing training experiences.

Once finished viewing the directions video, participants used another link (again sent privately through the Zoom chat) to the collaborative Miro board for the first task, Task 1 / Map 1. During this task each participant had their own Miro boards, and kept their computer cameras off, and their computer microphones muted. This prevented any participant interaction during the first task. Participants had fifteen-minutes to complete the first task. If one participant finished before the other, they were asked to wait until the other participant had finished.

When both participants were finished (or when fifteen-minutes had passed), their access to their Miro boards was terminated. The directions video for the second task was then played on the researchers shared screen for the participants to watch together. Afterwards, participants were then sent a link to a second collaborative Miro board, which hosted Map 2. Here, participants in the dyadic conditions met the other member of the dyad for the first time. Participants in the individual condition with self-explanation found a second map and began narrating their thoughts and activities. Participants in individual condition without explanation found a second map and began working without experiencing social interaction. Participants had fifteen-minutes to complete the second task.

Once Task 2 was complete, participants were then sent a third, private, individual link to Task 3, the post-task and assessment of transfer learning. Task 3 consisted of five smaller network design puzzles, each with their own small paragraph of directions. Once participants completed Task 3, they clicked on a link on their Miro board that took them to the post-task questionnaire hosted on Qualtrics.

Results

Regarding task performance for dyads (N=98) and individuals (N=77), results suggest that dyads do not outperform individuals on the network design problem-solving task. There is no significant difference in length of the total network submitted for Map 2 between dyads and individuals, $t(173) = .838$, $p = .403$, $d = 9.923$. Findings from the two-by-two factorial ANOVA show no interaction between distributed experience (knowledge diversity) and assigned task roles in regards to performance, $F(1, 97) = .388$, $p = .535$; nor was there a main effect of distributed experience from a training task (also referred to as knowledge diversity) on performance, $F(1, 97) = 1.864$, $p = .450$; nor was there a main effect of assigned task roles on performance, $F(1, 97) = .576$, $p = .175$.

Regarding learning outcomes for individuals from all conditions (N=273), results suggest that individuals who worked in a dyad do not show a greater frequency of transfer learning than individuals who did not work in dyads. This is evidenced by the fact that there is no significant difference in total transfer success between dyads and individuals, $t(271) = -.459$, $p = .647$, $d = 1.299$. There is also no significant difference in total transfer error between dyads and individuals, $t(5) = -.441$, $p = .677$, $d = .742$. Findings from the ANOVAs of learning show no interaction between distributed experience (knowledge diversity) and assigned task roles in regards to learning outcomes, $F(1, 195) = 1.135$, $p = .288$; nor are their main effects of distributed experience from a training task on learning outcomes, $F(1, 195) = .223$, $p = .637$; nor are there main effects of assigned task roles on learning outcomes, $F(1, 195) = .453$, $p = .502$.

Discourse Characteristics

At the group level, dyads spent an average of 9.5 minutes (SD = 4.162) on the collaborative task (range, 2.36 - 19.41 minutes), but the distribution was bimodal, with a cluster of conversations centered at about 5 minutes length and another more dispersed cluster at about 12 minutes. Table 2 displays the discourse characteristics total time (minutes) spent speaking during the main task and total number of speaking turns taken by study conditions in which participants spoke.

Table 2: Discourse characteristics by condition.

Study Conditions	Time Speaking		Number of turns taken	
	M	*SD*	*M*	*SD*
Indiv. Self-Explanation	7.19	3.70	40	27.07
Joint without Roles	9.19	4.16	95	39.43
Joint with Roles	9.84	3.87	95	39.78
Distributed w/out Roles	11.43	3.45	120	37.34
Distributed with Roles	10.78	3.65	111	40.78

There is no overall significant difference in these discourse characteristics among conditions, perhaps because of the bimodal distribution of discourse durations. But on average, participants in the knowledge distributed conditions (DW and DR) spent more time speaking and used a greater number of turns than participants in the joint or shared knowledge conditions (JW and JR) or participants in the individual work self-explanation condition (IE).

The frequency of explanations, the speech act of primary interest in the current study, correlates with the frequency of each of the other speech acts. In fact, almost all speech acts in this study correlate with each other. There are a couple possible explanations for these relationships. First, high correlations may have arisen from covariation in the length of many of the dialogues. Another possible explanation for these high correlations may be the presence of one or more latent variables. Principal component analysis (PCA) revealed two components. The first component is dominated by *explanation* and *coordinating joint attention*. Prior research associates both with cognitive elaboration (Chi et al., 1989; Roschelle & Teasley, 1995; Webb, 1989), and work by Roschelle & Teasley (1995) suggests that these two terms should be linked. The second component is dominated by *response modify*, *social facilitation*, and *response agree*. Each of these speech acts have a social effect of continuing the conversation, either by engaging in discussion of modifications, expressing socially positive behaviors, or by agreeable responses. Interestingly, Component 1 correlates with transfer learning, $r = .173$, $p = .015$, while Component II does not, $r = -.092$, $p = .200$.

Regarding differences among the study conditions in dyadic communication, specifically the frequency of explanations, findings from the two-by-two factorial ANOVA of explanations show a significant effect of distributed experience induced via the training task (knowledge diversity) on the frequency of explanations, $F(1, 98) = 8.142$, $p = .005$ (see Figure 2). There was no effect of assigned task roles on explanations, $F(1, 98) = .160$, $p = .690$; nor was there an interaction between distributed experience (knowledge diversity) and assigned task roles, $F(1, 98) = .544$, $p = .462$.

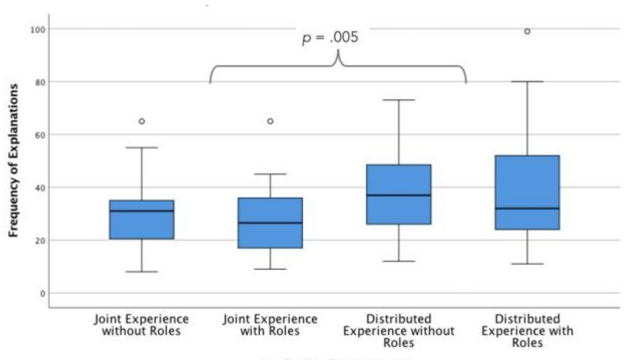

Figure 2: Box plots of the frequency of explanations used in each dyadic condition.

Explanations that occur during dyadic group work have a weak association with task performance that is approaching significance, $r = -.157$, $p = .066$ (N=98). Recall that in the current study, a negative correlation with network length is an indicator of a positive relationship with task performance, because the aim of the problem-solving task is to minimize the total length of the network.

Explanations that occur during dyadic group work have a positive correlation with transfer learning, $r = .258$, $p < .001$. Because the measure of transfer learning is a post-task questionnaire taken by individuals, this analysis is conducted at the level of individual members of the dyads (N=273).

Discussion

The current study addresses the question of whether two strategies of effective cooperative learning activities – ensuring group knowledge diversity and assigning task roles – positively affect group task performance or individual learning outcomes from an online virtual collaborative problem-solving task. The current analyses offer three main findings, which together establish an indirect pathway from group knowledge diversity to learning and transfer. First, group knowledge diversity – introduced through a training task – tends to positively affect the frequency of explanations during dyadic discourse regardless of the assignment of task roles. Second, explanations uttered during dyadic discourse are positively associated with learning outcomes and, to a lesser degree, with group task performance. Third, frequency of self-explanation is not associated with performance or learning outcomes. Each of these findings is briefly discussed below.

Knowledge Diversity

The current study enhanced knowledge diversity in a dyad by way of a training task. Participants who experienced a different training task than their partner were more likely to use explanations during their collaborative discourse than participants who instead experienced the same training task. This relationship between group knowledge diversity and explanations persisted regardless of whether the group's knowledge diversity was made explicit through the assignment of task roles.

Why did this happen? Why might the cognitive manipulation of knowledge diversity have motivated explanations to a greater degree than the social manipulation of assigned task roles? One reason may be that, in the context of the collaborative network design task, the implementation of the social manipulation may not have had the anticipated effect. Instead of making the dyad's knowledge diversity explicit, it may have simply distributed task responsibilities among group members. In other words, role assignments may have been interpreted as action-based roles (i.e., the road builder's task was to *build* roads), rather than roles designed to spark explanations (i.e., the road builder may not have seen a need to *explain* how to build a road).

A second reason may be that the cognitive manipulation of group knowledge diversity created an authentic need for explanation and information exchange. The need may have arisen as participants realized they had different experiences during the pre-task. The work to coordinate a shared understanding would have required explanations. The need for explanations may also have arisen as participants attempted to agree upon a single solution, and realized they disagreed. The work to reconcile their disagreement would have required information exchange.

This second reason is consistent with the literature on group diversity (c.f. Hong & Page, 2004; Jeppesen & Lakhani, 2010; Page, 2014; Surowiecki, 2005), which demonstrates (both theoretically and empirically) that group diversity increases the frequency of proposed novel solutions, which can increase the frequency of innovation and thus group performance. Diverse groups tend to out-innovate and thus out-perform homogeneous groups, even expert homogenous groups (Surowiecki, 2005). Importantly, this enhanced success for diverse groups hinges on their ability to communicate and exchange information. Thus, positive effects of group diversity on performance are mediated by information exchange (Homan et al., 2007).

Interestingly, results from the current study were achieved with a knowledge diversity *manipulation* and did not stem from a diversity of prior knowledge or expertise of group members. This is a contribution to the literature, because it shows that the benefits of group diversity (and the "wisdom of crowds") is not inherent to a group's composition but can be catalyzed by an intervention or experience (i.e., a training task). This result may be key to understanding why some cooperative learning intervention techniques are more effective than others. Further research is needed to generalize this finding beyond a network design problem-solving task.

Explanations

The current study finds that explanations are positively associated with learning outcomes, and to a lesser degree with group task performance. This finding suggests that explanations observed in the current study may be associated with cognitive elaboration. Cognitive elaboration is a mental sense-making activity presumed to occur because of cognitive demands of dialogue as one explains one's memories, actions, or thoughts to another person.

However, the current study found a relationship between explanations and learning only in dyadic conditions. In other words, explanations were associated with transfer learning when they were uttered in a group setting, but not for the individual conditions. This is inconsistent with the literature on cognitive elaboration, which extensively documents learning effects from self-explanation (Lombrozo, 2006).

The effect of group discourse on individual learning may be the result of a cognitive mechanism that occurs in social settings, described by Roschelle and Teasley (1995), as coordination of knowledge or "knowledge coordination" - an exchange of meaning through language to introduce, monitor, and repair a shared understanding (also Kuhn, 2015; Schober & Clark, 1989; Voiklis & Corter, 2012; Wilkes-Gibbs & Clark, 1992). Knowledge coordination is also described as a probing of another's mind, increasing exposure to new ideas and thus positively affecting learning outcomes (cf. Azmitia, 1988; Bos, 1937; Brandon & Hollingshead, 1999; Johnson & Johnson, 1999). Attention to the mind of another has long been understood to play an important role in consolidating knowledge (Webb, 1985). And the effectiveness of this coordination process as an educational tool has been well documented in the literature on peer tutoring (Devin-Sheehan et al., 1976; Fantuzzo et al., 1992; Ortiz et al., 1996).

Discourse during collaboration can also result in the co-construction of new knowledge. Co-construction happens when individuals collaboratively build knowledge and develop strategies that no group member had in advance of the problem-solving task (Webb, 2009). It is a process of sharing, seeking clarity, offering corrections, drawing connections, and building on each other's ideas and perspectives (Hogan et al., 2000; Schwartz, 1995).

Interestingly, in the current study, PCA of dyadic discourse revealed two components; a knowledge coordination component (dominated by *explanation* and *coordinating joint attention*), which correlated with transfer learning, and a social discourse component (dominated by *response modify*, *social facilitation*, and *response agree*), which had no relationship with transfer learning. Together these discourse components may form a "cognitive ecology," described in distributed cognition theory (Perry, 2003) as the environmental, social, cultural, and historical elements of the context of the group that motivate and influence group interactions. The work to organize these cognitive and social aspects of group work may play an important role in the learning outcomes of individuals within a group.

Conclusions

Effective cooperative learning methods like the Jigsaw (Aronson et al., 1978) tend to apply two strategies in tandem to encourage learning: enhanced group knowledge diversity and assigned task roles. The current study finds that group knowledge diversity, and not assigned task roles, is key to fostering more explanations during collaborative dyadic problem-solving work in virtual settings. The knowledge diversity examined in this study was induced using a training task that predisposed members of a dyad to different perspectives and solutions to the same problem, thus distributing the necessary problem-solving strategies among both members of the dyad. This distributed knowledge fostered a quality of explanations associated with learning outcomes. The findings show that the frequency of explanations mediates an indirect relationship between group knowledge diversity and individual learning outcomes.

These results suggest that knowledge diversity can be manipulated with a training task to positively affect learning outcomes, if explanations and social discourse can freely occur to coordinate knowledge; however, generalizations from these findings are limited due to the relatively homogeneous sample population and the specific network design task used to stimulate collaborative problem-solving. Future research should seek to replicate these findings in authentic classroom settings (both virtual and physical) and use multivariate analysis coupled with natural language processing techniques to more thoroughly examine the speech patterns that comprise explanations used during collaborative group work and self-explanations.

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