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Effects of prior knowledge on collaborative and individual learning

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ABSTRACT

Collaborative learning is an extensively used instructional technique by which individuals interact in small groups to learn to solve academic problems. This study aimed to determine the impact of task-specific prior knowledge on individual learners and collaborative groups that were instructed to collaborate. A 2 (individual vs. collaborative group) × 2 (novice vs. knowledgeable learners) factorial experiment with 228 students was carried out to examine the effects of these treatments on performance and mental effort in learning and its outcomes. As expected, knowledgeable individuals and knowledgeable collaborative groups outperformed novice individuals and novice collaborative groups in learning outcomes. Less knowledgeable, collaborating learners outperformed less knowledgeable, individual learners in learning outcomes. While more knowledgeable collaborating and individual learners performed equally well in the learning phase and the delayed test, on the retention test, collaborative groups demonstrated better performance. In general, collaboration benefited learning compared to individual learning in complex tasks, but performance depended on the learner task-specific prior knowledge.

1. Introduction

Collaborative learning is an extensively used instructional technique. It refers to the process by which individuals interact in small groups to learn to solve academic problems (Slavin, 2014). However, literature indicates that learning in groups is not always associated with better learning compared to individual learning (Clinton & Kohlmeyer, 2005; Morgan & Tindale, 2002; Shibley & Zimmaro, 2002; Tindale, 1993; Weldon, Blair, & Huebsch, 2000).

This article begins with a short discussion of the importance of developing effective collaborative groups (i.e., team formation) and reveals that the results of research in this area are inconclusive. That being said, from an instructional perspective data indicate that providing explicit guidance on how to collaborate on highly demanding tasks may help collaborative groups to take advantage of inter-individual activities for learning. The discussion on developing collaborative groups is followed by a review of collaborative learning research from a cognitive load theory (CLT) perspective (Sweller, Ayres, & Kalyuga, 2011). The experiment carried out here examined whether, taking prior knowledge into account, collaborative groups are more effective than individual learners when they are prepared to learn collaboratively with highly-complex tasks. Groups were prepared for collaboration via explicit guidance on how to work together considering the characteristics of the tasks.

1.1. Promoting successful collaboration

One way to maximize collaborative learning is to develop collaborative groups to be effective. Research on team development suggests that a collaborative group is effective when it develops shared mental models, mutual performance monitoring, and interpersonal trust (Fransen, Kirschner, & Erkens, 2011), positive social interdependence (D. W. Johnson & Johnson, 2009) or social cohesion (Sharan & Sharan, 1992). This assumes that high-performing groups require extensive periods of time (Gersick, 1988; S. D. Johnson, Suriya, Won Yoon, Berrett, & La Fleur, 2002). However, research shows that collaborative group development is not always associated with higher performance. For example, concerning cohesion (i.e., the progressive tendency for a group to stick together in the pursuit of instrumental goals), a meta-analysis showed that the cohesion-performance relationship was stronger for tasks requiring high interdependence such as communication, coordination, and mutual performing monitoring (Gully,

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Devine, & Whitney, 2012). However, a subsequent meta-analysis reexamining this relationship found that cohesion had a lower effect size with increasing performance, decreasing even further when the measure of cohesion was more general (Castaño, Watts, & Tekleab, 2013).

From an instructional perspective, there is also evidence that suggests that learners can take advantage of collaborative work when they receive guidance on how to collaborate rather than waiting for collaborative groups to develop naturally. For example, Buchs, Gilles, Antonietti, and Butera (2015) used 10 min to instruct group members on collaborative skills. They found that learning in dyads with instructional support on how to work together produces better learning outcomes compared to learning individually or collaboratively without instructional support. Prichard, Bizo, and Stratford (2006) examined the benefits of guiding collaborative members on how to work in groups with three cohorts. In general, they found that the cohort that received instructions on how to collaborate outperformed the cohort that was not trained and that the benefits of the collaboration guide could be lost when the collaborative group members split up into new groups.

Group development and instructional approaches have in common that collaborative groups should have some experience or guidance in working together. A factor in this might be task complexity as a determinant of the effectiveness of learners who have been prepared to collaborate compared to individual learners. Task complexity is a concern that has been extensively studied within a CLT framework.

1.2. Collaboration from a cognitive load theory perspective

CLT is an instructional perspective based on human cognitive architecture (Sweller, Van Merriënboer, & Paas, 2019). It suggests that when acquiring and automating complex knowledge (e.g., school domains) instructors should provide proper guidance keeping task complexity within working memory capacity which can be as low as two elements (Gilchrist & Cowan, 2011) and considering whether long-term memory structures facilitate or impair learning (Kalyuga, Ayres, Chandler, & Sweller, 2003). Cognitive load refers to the load on working memory when processing information (Sweller et al., 2011). CLT researchers have presented evidence that students learn better when they process task information within the boundaries of working memory (Sweller et al., 2011). If tasks are complex and little knowledge is stored in long-term memory, learners experience overload and performance decays.

Collaborative learning is an emerging research topic in CLT. Under some circumstances group interactions can be a source of cognitive load associated with a collaborative learning task (P. A. Kirschner, Sweller, Kirschner, & Zambrano R., 2018). However, evidence of the advantages of collaborative learning compared with individual learning is not always consistent. On the one hand, there is evidence that a collaboration-based approach may be more beneficial than individual learning when problems are highly complex and when information is distributed among different working memories. Investigations by F. Kirschner, Paas, and Kirschner (2009, 2011; 2011) suggest that groups may be more effective and efficient because members can make use of each other's working memory resources (the collective working memory effect; F. Kirschner, Paas, & Kirschner, 2011). The collective working memory effect holds that collaborative learning is more effective than individual learning when the complexity of the learning material is high (F. Kirschner, Paas, & Kirschner, 2011). Sharing information processing of learning materials among the collaborative group members who share working memory resources permits better comprehension and knowledge acquisition of the to be learned tasks. This effect seems to occur when the benefits of reducing cognitive load due to information distribution (i.e., making learners depend on each other's information) are higher than the cognitive costs incurred in communication and coordination activities (i.e., transactional activities). F. Kirschner, Paas, and Kirschner (2011) also found that for low-complexity tasks, collaborative learning was redundant since group members achieved equal or lower performance and efficiency scores than individuals. An interesting result in F. Kirschner, Paas, and Kirschner (2011) is that group members perceived a higher perception of mental effort in the learning phase which was related to a higher performance and efficiency on the posttest.

On the other hand, evidence suggests that collaboration does not improve learning either low- nor high-complexity tasks compared with individual learning. Investigations by Retnowati, Ayres, and Sweller (2010, 2016) investigated the effect of conventional problems and worked-out examples (worked examples) on individual and collaborative learning. They found that in some high-complexity tasks, individuals performed better than groups. They also found that working in collaborative groups was more beneficial than working alone in problem-solving tasks. In general, Retnowati et al. concluded that at least under some circumstances, especially when using worked examples collaborative learning is not better than individual learning either in high or low complex tasks. Unlike the Kirschner et al. study, task information was not distributed among members in these studies. Curiously, in the learning phase of the second experiment (Retnowati, Ayres, & Sweller, 2016), individual learners outperformed groups in high-complexity tasks with a significantly higher cognitive load.

When considering prior knowledge, there are also mixed results. Zhang, Kalyuga, Lee, Lei, and Jiao (2015) explored collaborative learning when grouping learners by their scores of the previous year. Learners with lower scores were collaboratively grouped and categorized as less knowledgeable learners (with lower prior knowledge), and those with higher score as advanced learners (higher prior knowledge). The latter did not receive instruction on the domain-specific learning task. Researchers found that heterogeneous groups (i.e., groups including novice and advanced learners) favored lower prior knowledge learners, whereas for more knowledgeable learners, homogeneity was redundant. Moreover, individuals with higher prior domain knowledge marginally outperformed homogeneous and heterogeneous groups. Zhang, Kalyuga, Lee, and Lei (2016) replicated this study and obtained similar results. These studies are limited because novice and advanced students were not grouped using prior knowledge specifically related to the learning tasks.

Retnowati, Ayres, and Sweller (2018) performed a study manipulating prior knowledge of learning tasks. Participants had either incomplete or complete prior knowledge and compared collaborative groups with individual learning. Interaction analyses revealed that when learners have gaps in their knowledge base, collaborative learning is superior to individual learning. However, when learners have complete prior knowledge, individual learning is superior to collaborative learning. They also found that individual learning condition participants with complete prior knowledge for all learning tasks (individual-complete knowledge condition) outperformed collaboration with complete and incomplete knowledge and individual with incomplete knowledge conditions in transfer tasks. However, the researchers did not compare complex and simple tasks. It is not yet clear whether these results would vary if the complexity of the tasks is increased to the point that individual learners with complete prior knowledge still need to rely on other group members' working memory resources.

Considering prior knowledge in collaborative learning also can pose challenges in predicting cognitive load. If group members are advanced, learning collaboratively may be harmful because transaction activities demand working memory resources resulting in increases in cognitive load. However, if the task has a very high level of interactive elements and peers have partially developed previous knowledge, it can be expected that the collaboration is beneficial. Thus, demands on working memory may increase if collaboration is unnecessary and decrease if collaborating partners have useful knowledge with group members taking advantage of partially developed schemas to refine their knowledge in a learning situation (i.e., reexposure effect; Rajaram & Pereira-Pasarin, 2010). These two opposing effects on working memory demands may counteract each other.

1.3. The present study

Task complexity, information distribution (member interdependence), and prior knowledge are factors that may explain the advantage of collaborative learning. However, the inconclusive results seem to suggest that grouping learners to collaborate does not necessarily promote better learning (Gillies, 2016). Also, currently there are no data from CLT-based studies about preparing groups to collaborate (see section 1.1).

Instructing students how to work collaboratively on specific tasks may be a category of domain-generalized knowledge (Kalyuga, 2013) at the group level (P. A. Kirschner, Sweller, Kirschner, & Zambrano, 2018). Knowledge about how to collaborate may work better when it is built into a domain-specific task. When this type of knowledge is learned in task-specific situations, it may be retrieved from long-term memory and used in similar tasks through analogical transfer (Gick & Holyoak, 1980). For example, a group of learners may better learn problems of linear demand and supply curves in an administration subject if they previously learned to solve problems of linear equations in mathematics compared to another group of learners who did not work on mathematics tasks as a team. Group members may transfer their experience from one task situation to another by finding correspondences through schema induction (Gick & Holyoak, 1980). Generalized domain-knowledge on collaborative work may explain why learners who are prepared to work together are more effective than individual learners (Buchs et al., 2015; Prichard et al., 2006).

This study is a first step to attempt to close this gap. Accordingly, this experiment examined the effect of learning in groups instructed to collaborate vs. learning individually and the effect of prior knowledge level on performance and mental effort with high-complexity problems.

The hypotheses were:

H1. When learning individually, students with more knowledge will outperform and invest less mental effort than students with less knowledge.

H2. When learning in collaborative groups, students with more knowledge will outperform students with less knowledge but the counteractive effects on mental effort when more and less knowledgeable students collaborate cannot be precisely determined.

H3. For learners with less knowledge, collaborative learning groups will outperform and perceive less mental effort than individual learning groups.

H4. For learners with more knowledge, learning in collaborative groups will become detrimental and no advantage to learning in collaborative groups will be found.

2. Method

2.1. Participants

This study was conducted with 228 students (135 females, 93 males) of a large, public high school in Sangolquí, Ecuador. Their average age was 15.87 years (SD = 0.745). The study was part of the mathematics classes and received approval from the local ethical committee. Participants did not have prior knowledge of the learning phase tasks because it is not included in the content of the very strict national curriculum which explicitly prohibits teaching topics not in the curriculum. Further, teachers at the school confirmed that they had not previously taught the content of the learning tasks and that all participants came from the same school. Finally, participants were randomly assigned to the conditions to exclude any systematic prior knowledge differences. Participants were notified of the study and received academic compensation of 10 points for voluntary participation.

2.2. Design and procedure

A 2 (collaborative learning vs. individual learning) x 2 (less vs. more knowledgeable learners) factorial design was used. Dependent variables were performance and mental effort. The study was conducted in five phases: preparation, prior knowledge instruction, learning, retention testing, and delayed testing. Each phase consisted of multiple sessions of 45 min. Three instructors and the experimenter guided participants throughout all phases of the study. The experimenter supervised the procedure to guarantee intervention fidelity. All instructions were read aloud.

The five phases entailed:

1. *Preparation*: Construct collaboration schemas using the previously learned domain-specific task of solving quadratic equations and emphasizing collaborative work. Half of the participants formed 3-person collaborative groups (collaborative group condition), and the other half worked individually (individual condition). This phase consisted of four sessions over one week.
2. *Prior knowledge instruction*: Half of each of the collaborative group and individual conditions received instruction on how to calculate a break-even point (BEP). This phase comprised one session on the day following the preparatory phase.
3. *Learning*: All participants received the same learning tasks to calculate the BEP either as individuals or in teams. This phase comprised one session on the day following the prior knowledge instruction phase.
4. *Retention testing*: Similar problems with only the name of the costs and their values varied from the learning tasks were used to evaluate the outcomes of the collaborative and individual learning conditions one day after the learning phase.
5. *Delayed testing:* Similar retention testing problems but seven days after the learning phase.

The *preparation phase* began in the second week of the new school term, after two months of school vacation, to reduce effects of having previously worked together. Participants were randomly assigned to two conditions: individual learning and collaborative groups. All learners worked on solving quadratic equations. There were no time restraints on the first tasks, but 10 min were allotted to solve the final two tasks from the second session onwards (a digital clock was placed in front of the class); writing was permitted only for the final answer. Instructors encouraged members to interact with each other, to share their values and coordinate calculations among themselves, and discouraged non-task conversations. Participants received the correct answers at the end of each session and were asked to think about how they may collaborate better on the following tasks.

In the *prior knowledge instruction phase*, half of the participants were randomly selected to receive additional instruction. Each learner received a booklet with the concepts of the BEP and a worked example on how to solve a problem (8 min). After studying the booklet, they solved three conventional problems individually (7 min each) using the worked example of the booklet as assistance. After solving each problem, they received the worked example of the three problems and were asked to compare their results and correct their mistakes. Moreover, learners were asked if they had questions to clarify any step for calculating the BEP. Instructors made sure all learners had corrected the errors to foster problem-solving understanding. The other half of the participants received a theoretical class about the topic of the new term, real number properties, which was unrelated to the BEP.

In the *learning phase,* only individuals and groups that had completed the previous phases participated. An a priori analysis with a power of .8 and a medium-size effect (i.e., 0.06; Cohen, 1998) revealed that the study required 32 individuals for the individual learning condition or 11 triadic groups for the collaborative learning condition to reliably test the hypotheses (see Results section). Collaborative group members remained in their groups to maintain the previous schemas of working together (Prichard et al., 2006). Groups and individuals worked on three tasks to calculate the BEP (9 min for task 1, 8 min for tasks 2 and 3 = 25 min). As in the preparation phase, the instructors encouraged group members to share their values and to coordinate the calculations to solve each problem. If a collaborative group or individual solved the task before the time assigned, that group or individual was required to wait to start the next problem. All problems were solved mentally. Using paper and pencil was only permitted for recording the final answer and indicating the mental effort after completing each task.

In the *retention* and *delayed* test phases, participants were required to individually solve three conventional problems in 30 min, 10 min per problem. They were asked to write the calculations for each step of the problems and scored the amount of mental effort invested in each problem. If a student was absent from the retention test, s/he was allowed to take the delayed test and vice-versa because each test was analyzed independently. No case, thus, needed to be deleted.

2.3. Materials

The materials were in the domain of mathematics and economics. The preparation phase consisted of solving quadratic equations, while the remaining phases involved calculating BEPs. All materials were paper-based and presented in booklets.

2.3.1. Preparation phase

Quadratic equations are compulsory in the national curriculum, and the participants had already received instruction the previous year. All tasks were designed and assigned with a completion strategy scaffolding approach (Van Merriënboer, 1990) as follows: the first session began with an introduction about quadratic equations and two worked examples showing how to solve them using the factoring method during prior knowledge activation. Five rules on how to solve the equations collaboratively were given and explained to the collaborative group condition, followed by a worked example showing how each group member should apply them (see supplementary material), and a conventional task with the correct answer. Examples of the rules are: When it is possible to perform the calculations without the help of others, do it alone and continually rehearse the results to avoid forgetting them. For the collaborative group condition, we manipulated the task information, unpacking the equation values to distribute them among group members (e.g., for $-45x^2$, each member would receive $-15x^2$), requiring each learner to depend on other members to solve the problem. This manipulation also had the purpose of providing prior experience for the information distribution of the learning tasks. Each member received different values for solving the same equation and a table in which they could write down the intermediate steps (see supplementary material). The individual condition participants received the same values and the table.

In the second session, both conditions received the rules of collaboration, two conventional problems with correct answers, and a conventional problem without the correct answer again. The conventional problems had six values, two for each group member; individuals received all values. In the third and fourth sessions, both collaborative groups and individuals received three conventional quadratic equation problems without correct answers, with six to nine values (e.g., $-10 + 5x^2 - 50 - 50 + 200x = 1x - 50x^2 + 50x + 100x^2$).

2.3.2. Prior knowledge instruction phase

One way to acquire generalizable domain-specific collaboration schemas may be to use different tasks but with analogous features. Calculating the BEP is a problem with similar characteristics to quadratic equations such as: requiring a combination of several numerical values, using basic mathematical operations, calculating partial answers, holding them in working memory, and finding a single correct answer. The material included a brief explanation of the BEP and a worked example (see Table 1 and steps in Table 2). It also included three conventional problems that were similar to those used in the learning phase, and their corresponding resolution process (worked examples).

Table 1
Example a BEP problem.

Calculate the break-even point of a school chairs business:
- Total chairs produced: 50
- Price of each chair: $41
- Office and warehouse rental: $108
- Cost of the wood for the chairs: $155
- Administrator's salary: $119
- Cost of the metal for the chairs: $63
- Profit: $ 52
- Cost of the paint for the chairs: $82
- Electricity, water, telephone, and Internet service: $71

2.3.3. Learning phase

Each participant received the concepts of the BEP, two worked examples, prompt questions, three learning tasks, and a piece of paper with examples of fixed and variable costs and the BEP in unit's formula (see step 6, Table 2). The booklet explained the BEP and the types of costs (i.e., fixed and variable costs, variable cost per unit, and total costs), the contribution, and the BEP both in units and sales. The worked examples contained a 7-step procedure (see Table 2). Examples of prompt questions were: What was the difference between the BEPs in units and sales? How did you calculate the contribution? Examples of fixed and variable costs were provided to avoid confusion during the learning phase.

Participants from the collaborative group and individual conditions received the same learning tasks. Task complexity level was determined using the method of Sweller and Chandler (1994), which counts the number of items and operations that must be considered and processed in working memory to solve the task. As presented in Table 2, the 7-step procedure to solve each problem comprised nine items that must be integrated during 8 min to obtain a single correct answer (Table 2). Like the equations of the preparation phase, no step could be solved without all members sharing and working together on their items. Each member needed to depend on other's information. A group member received a fixed cost, a variable cost and any of the other three items that were insufficient to solve each step of the problem. Members had to share all their items, coordinate how to solve each step, and jointly perform calculations using basic mathematical operations. Each step varied in the number of interacting items (column 3 of Table 2), amounting to a total of 45 including mathematical signs. Also, in each step, individual participants and collaborative groups had to perform multiple mental calculations to find many partial answers, hold them temporarily in working memory (column 4 of Table 2), and then integrate them with partial answers computed by others in the group without writing the calculations (i.e., mental arithmetic; DeStefano & LeFevre, 2004). Given these cognitive demands, it was assumed that the tasks were highly complex.

2.3.4. Retention and delayed test phases

The quality of the task-specific knowledge of each participant was assessed using six similar problems with the same level of complexity as the learning tasks. Participants received worksheets with three tasks one day after the learning tasks (the retention test) and three other similar tasks seven days after (the delayed test). Each problem included a table with seven numbered rows to write the calculations for each step of the solution process.

Table 2
Process to calculate the BEP.

Steps to solve the problem	Calculations	Interacting elements	Temporary answers maintained in working memory
1. Recognize cost items	Nine items of the problem 155, 63, 82, 50, 41, 108, 71, 119, 52	9	
2. Total variable cost	$VC_1 + VC_2 + VC_3 = TVC$ 155 + 63 + 82 = 300	7	300
3. Variable cost per unit	TVC ÷ amount produced = CU 300 ÷ 50 = 6	5	300, 6
4. Contribution	Price – CU = C 41–6 = 35	5	6, 35
5. Total fixed cost	$FC_1 + FC_2 + FC_3$ + profit = TFC 108 + 71 + 119 + 52 = 350	9	35, 350
6. BEP in units	TFC ÷ C = BPU 350 ÷ 35 = 10	5	35, 350, 10
7. BEP in sales	BPU × price = BPS 10 × 41 = 410	5	10, 410

Note. CV = variable cost; FC = fixed cost; TVC = total variable cost; CU = variable cost per unit; C = contribution; TFC = total fixed cost; BPU = BEP in units; BPS = BEP in sales.

Table 3
Means and standard deviations for dependent variables in the learning phase.

Dependent variables	Collaborative groups		Individuals	
	M	SD	M	SD
Learning performance (0–1)				
Less knowledgeable learners	.51	.31	.25	.29
More knowledgeable learners	.84	.20	.65	.24
Learning mental effort (1–9)				
Less knowledgeable learners	6.27	2.06	6.41	1.58
More knowledgeable learners	6.99	1.68	5.51	1.87

2.4. Measurement

2.4.1. Cognitive load

Cognitive load was measured subjectively in the learning, retention test, and delayed test phases using a 9-point mental effort rating scale (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). Mental effort "refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task; thus, it can be considered to reflect the actual cognitive load" (Paas et al., 2003, p. 64). The scale is non-intrusive, is sensitive to changes in complexity, and is valid, and reliable for individual learning (Szulewski, Gegenfurtner, Howes, Sivilotti, & van Merriënboer, 2017). Participants were asked to 'Please rate the level of mental effort you invested in this task' on a Likert scale ranging from 1 (very, very low mental effort) to 9 (very, very high mental effort) after each problem to obtain a more precise estimation of the invested load (Van Gog, Kirschner, Kester, & Paas, 2012). Cognitive load for each collaborative group for the learning phase was calculated averaging the scores of the members. Individual scores were used in subsequent phases.

2.4.2. Performance

Performance was measured in the learning, retention test, and delayed test phases. The total number of points for all three learning tasks was 3: 1 point per correct answer or 0 points if the answer was incorrect. For the three tasks of the retention test and delayed test, a total of 7 points could be awarded based on the seven calculations required to obtain the BEP. Each calculation was scored individually based on whether correct values and mathematical operations were used. Correct calculations received 1 point and incorrect calculations 0 points, resulting in a maximum score of 21 points and a minimum of 0. If a step was partially correct, a proportional score was given (e.g., if in steps 4, 6 or 7 an incorrect value was used, ½ point was given). Performance scores on the learning, retention test and delayed test phases were transformed into proportions.

3. Results

The data were analyzed with 2 (collaborative group vs. individual learning) x 2 (less knowledgeable learners vs. more knowledgeable learners) analyses of variance (ANOVAs). Dependent variables were performance and mental effort, which were measured and analyzed separately for the learning, retention test, and delayed test phases. There were no activities or analyses carried out between the phases. Data exploration revealed outliers. However, the outliers were not excluded because an analysis that excluded outliers showed that they did not alter the pattern of significant results. The results are reported separately, and the means and standard deviations of the dependent variables for all phases are shown in Tables 2–4. A summary of all significant results is provided in Appendix A. A significance level of 0.05 was used for all analyses. Partial eta-squared was used as a measure of effect size, with values of 0.01, 0.06, and 0.14 corresponding to small, medium, and large effects, respectively (Cohen et al., 1988).

3.1. Learning phase

Two collaborative groups and two individuals were excluded from the analysis after not completing the previous phases. In this phase, 17 three-person novice collaborative groups, 19 knowledgeable collaborative groups, 66 less knowledgeable individuals, and 46 more knowledgeable individuals participated. Table 3 shows descriptive statistics.

Concerning performance, the ANOVA revealed a significant main effect for condition, $F(1, 144) = 18.391$, MSE = 0.073, $p < .001$, $\eta_p^2 = 0.113$: collaborative groups ($M = 0.69$, $SD = 0.31$) outperformed individual learners ($M = 0.42$, $SD = 0.34$). The main effect for knowledge level was also significant, $F(1, 144) = 49.265$, MSE = 0.073, $p < .001$, $\eta_p^2 = 0.255$: knowledgeable learners ($M = 0.71$, $SD = 0.25$) outperformed novice learners ($M = 0.31$, $SD = 0.31$). The interaction

Table 4
Means and standard deviations for dependent variables in the retention test phase.

Dependent variables	Collaborative groups		Individuals	
	M	SD	M	SD
Retention test performance (0–1)				
Less knowledgeable learners	.50	.22	.23	.22
More knowledgeable learners	.87	.18	.74	.24
Retention test mental effort (1–9)				
Less knowledgeable learners	6.01	2.50	3.86	2.29
More knowledgeable learners	5.67	1.87	6.12	1.62

between main effects was not significant; $F(1, 144) = 0.417$, MSE = 0.073, *ns*.

For mental effort, the main effect for condition was significant, $F(1, 144) = 4.006$, MSE = 3.052, $p = .047$, $\eta_p^2 = 0.027$: collaborative groups ($M = 6.65$, $SD = 1.88$) experienced more mental effort than individual learners ($M = 6.04$, $SD = 1.76$). However, the main effect for knowledge level was not significant, $F(1, 144) = 0.077$, MSE = 3.052, *ns*. The interaction between these effects was significant, $F(1, 144) = 5.849$, MSE = 3.052, $p = .017$, $\eta_p^2 = 0.039$. A post-hoc Bonferroni test showed that for participants learning individually, more knowledgeable learners reported less mental effort than less knowledgeable learners ($p = .008$, $\eta_p^2 = 0.048$). No differences were found for participants learning in collaborative groups. The test also showed no difference for less knowledgeable learners; however, for more knowledgeable learners, collaborative groups reported more mental effort than individuals ($p = .002$, $\eta_p^2 = 0.063$).

3.2. Retention test

In this phase, 49 novice collaborative group members, 56 knowledgeable collaborative group members, 61 novice individuals, and 46 knowledgeable individuals participated. Table 4 shows the descriptive results.

The ANOVA for performance found a significant main effect for condition, $F(1, 208) = 46.764$, MSE = 0.047, $p < .001$, $\eta_p^2 = 0.184$: collaborative groups ($M = 0.70$, $SD = 0.27$) outperformed individuals ($M = 0.45$, $SD = 0.34$). Concerning knowledge level, $F(1, 208) = 217.926$, MSE = 0.047, $p < .001$, $\eta_p^2 = 0.512$: more knowledgeable participants ($M = 0.81$, $SD = 0.22$) outperformed less knowledgeable participants ($M = 0.35$, $SD = 0.26$). The interaction between main effects was also significant, $F(1, 208) = 5.580$, MSE = 0.047, $p = .019$, $\eta_p^2 = 0.026$. The Bonferroni test showed that for participants learning individually, more knowledgeable learners outperformed less knowledgeable learners ($p < .001$, $\eta_p^2 = 0.414$); among participants learning in collaborative groups, more knowledgeable participants outperformed less knowledgeable learners ($p < .001$, $\eta_p^2 = 0.270$). It was also found that among more knowledgeable learners, collaborative groups outperformed individual learners ($p < .001$, $\eta_p^2 = 0.174$) and, for less knowledgeable participants, collaborative groups outperformed individual learners ($p = .002$, $\eta_p^2 = 0.044$). The large difference in effect sizes explains the significant interaction.

Regarding mental effort, a significant main effect for condition was found, $F(1, 208) = 8.524$, MSE = 4.443, $p = .004$, $\eta_p^2 = 0.039$: collaborative groups ($M = 5.83$, $SD = 2.18$) reported more mental effort than individuals ($M = 4.83$, $SD = 2.31$). Knowledge level was also significant, $F(1, 208) = 10.698$, MSE = 4.443, $p = .001$, $\eta_p^2 = 0.049$: more knowledgeable learners ($M = 5.87$, $SD = 1.77$) reported more mental effort than less knowledgeable learners ($M = 4.82$, $SD = 2.60$). The interaction between these effects was also significant, $F(1, 208) = 19.908$, MSE = 4.443, $p < 001$, $\eta_p^2 = 0.087$. The Bonferroni test showed that among participants learning individually, more knowledgeable learners reported more mental effort than less knowledgeable learners ($p < .001$, $\eta_p^2 = 0.126$). There was no significant difference between more and less knowledgeable learners on levels of mental effort when they learned in collaborative groups. In addition, among novice participants, collaborative groups reported more mental effort than individual learners ($p < .001$, $\eta_p^2 = 0.120$). However, for knowledgeable participants, no difference between individuals and collaborative groups was found, indicating the cause of the significant interaction.

3.3. Delayed test

In this phase, 49 novice collaborative group members, 57 knowledgeable collaborative group members, 65 novice individuals, and 44 knowledgeable individuals participated. Descriptive statistics are shown in Table 5.

Table 5
Means and standard deviations for dependent variables in the delayed test phase.

Dependent variables	Condition			
	Groups		Individuals	
	M	SD	M	SD
Delayed test performance (0–1)				
Less knowledgeable learners	.39	.14	.26	.20
More knowledgeable learners	.78	.23	.79	.22
Delayed test mental effort (1–9)				
Less knowledgeable learners	3.58	1.42	4.48	1.77
More knowledgeable learners	5.30	1.87	5.66	1.29

For performance, the main effect for condition was significant, $F(1, 212) = 4.467$, MSE = 0.041, $p = .036$, $\eta_p^2 = 0.021$: collaborative groups ($M = 0.60$, $SD = 0.27$) outperformed individual learners ($M = 0.48$, $SD = 0.33$). The main effect for knowledge level was also significant, $F(1, 212) = 271.491$, MSE = 0.041, $p < .001$, $\eta_p^2 = 0.562$: more knowledgeable learners ($M = 0.78$, $SD = 0.22$) achieved better performance than less knowledgeable learners ($M = 0.32$, $SD = 0.19$). The interaction between effects was significant, $F(1, 212) = 6.861$, MSE = 0.041, $p = .009$, $\eta_p^2 = 0.031$. For individual learning ($p < .001$, $\eta_p^2 = 0.464$) and for collaborative learning ($p < .001$, $\eta_p^2 = 0.311$), it was found that more knowledgeable learners outperformed less knowledgeable learners. The Bonferroni test indicated that less knowledgeable participants performed better in collaborative groups than those learning individually ($p = .001$, $\eta_p^2 = 0.053$); however, there was no significant difference between collaborative and individual groups explaining the significant interaction.

Regarding mental effort, the main effect for condition was significant, $F(1, 212) = 8.553$, MSE = 2.682, $p = .004$, $\eta_p^2 = 0.039$: individual learners reported more mental effort ($M = 4.98$, $SD = 1.70$) than collaborative groups ($M = 4.50$, $SD = 1.88$). The main effect for knowledge level was also significant, $F(1, 212) = 42.909$, MSE = 2.682, $p < .001$, $\eta_p^2 = 0.168$: more knowledgeable learners ($M = 5.48$, $SD = 1.65$) reported more mental effort than less knowledgeable learners ($M = 4.09$, $SD = 1.68$). The interaction between these effects was not significant $F(1, 212) = 1.189$, MSE = 2.682, *ns*.

4. Discussion

The results are discussed following the order of the hypotheses, starting with condition followed by level of prior knowledge. Regarding condition, it was expected that for individual learning, more knowledgeable learners would outperform and invest less mental effort than less knowledgeable learners (H1). In the learning phase, more knowledgeable individuals reported less mental effort than less knowledgeable learners as expected but performed equally well. In retention and delayed tests, more knowledgeable learners outperformed less knowledgeable learners as expected. Knowledgeable learners invested more mental effort in the retention phase and similar mental effort in the delayed test. This suggests that for high-complexity tasks, prior knowledge reduces mental effort during learning without necessarily improving performance during learning. However, as found by Retnowati et al. (2018), the benefits of providing prior knowledge for complex tasks had significant benefits in the performance outcomes (1 and 7 days after). Interestingly, in the retention test, novice individuals experienced a lower cognitive load. One possible explanation may be their lack of knowledge which may have reduced their judgment of the complexity of tasks and overestimated their current performance, which in turn decreased their mental effort ratings (Nugteren, Jarodzka, Kester, & Van Merriënboer, 2018).

We also expected that when students who have prior knowledge learn in collaborative groups, they will outperform less knowledgeable learners, but the counteractive effects on mental effort when more and less knowledgeable students collaborate cannot be precisely determined (H2). As expected, we found evidence for performance both in retention and delayed test phases. Advanced learners could handle the complexity due to their better task-specific knowledge. This result allows us to assume that transactional activities were advantageous for advanced learning groups because the learning tasks had a high level of element interactivity (Retnowati et al., 2018; 2016). This advantage was observed in both individual post-tests. For cognitive load, we found nonsignificant differences. Mental effect results suggest that transactional activities could have interfered with prior knowledge (Retnowati et al., 2018). Seemingly, collaborative groups of advanced learners experienced cognitive load caused by the redundancy of interactions that were unnecessary because group members already had partially developed task knowledge. This cognitive load may be equivalent to the low-knowledge groups' cognitive load. Low-knowledge groups may have performed irrelevant transactional activities (e.g., randomly searching activities) because they lack sufficient schemas that guide their operations in high-complexity tasks (Zhang et al., 2016).

Concerning the effect of prior knowledge, it was expected that when learners are less knowledgeable, collaborative groups outperform and perceive less mental effort than individuals (H3). We found evidence for this hypothesis on performance both in the retention and delayed tests. For cognitive load, surprisingly, less knowledgeable learners that learned in collaborative groups perceived a significantly higher load than individuals in the retention test while no difference was found in the other phases. In line with the collective working memory effect (F. Kirschner, Paas, & Kirschner, 2011), greater cognitive capacity allowed collaborative groups to acquire better mental representations from the complex information. These data suggest that when learners are required to learn from highly demanding problems, collaborative learning may impose a substantial cognitive load, but is more effective than in individual learning, and its benefits are observed in the long term (Soderstrom & Bjork, 2015). The perception of higher mental effort in the retention phase of learners who learned in collaborative groups is interesting ($M = 6.01$), but even more interesting is the substantially lower cognitive load perceived by individual students ($M = 3.86$). It seems, they did not invest a high mental effort because they did not have the appropriate task knowledge (Sweller et al., 2011). It may be necessary to investigate these cases in depth through the analysis of think-aloud protocols (Kalyuga & Plass, 2018).

It was also expected that when learners have prior knowledge, learning in collaborative groups will become detrimental, with no collaborative group advantage (H4). This was confirmed for all phases and measures except the performance in the retention phase of those who learned in collaborative groups. This result might be explained by the activating of prior task schemas when carrying out highly-complex tasks. During the learning phase, knowledgeable collaborative group members reported significantly higher cognitive load because they may need to reconcile their own knowledge with externally provided guidance (Kalyuga et al., 2003). Besides, they may have to deal with the transactional activities that were inevitable due to the distribution of information among members which further increased the perception of mental effort.

Interestingly, despite reporting more mental effort during collaborative learning, in the retention phase, more knowledgeable collaborative group members were more effective than more knowledgeable individuals. Seemingly, collaborative learning and prior knowledge for high-complexity tasks did not seem detrimental as the additionally acquired collaborative group knowledge allowed collaborators to outperform individuals the next day. However, this advantage was not long-lasting (i.e., in the delayed test).

5. Conclusions

In general, the results seem to suggest that collaborative learning may be effective for high-complexity tasks compared with individual learning when learners have domain-generalized knowledge at a collaborative group level (Kalyuga, 2013). Giving learners guidance on how to work together seems to be associated with better performance than just bringing students together to learn new problems (Gillies, 2016; P. A.; Kirschner et al., 2018). Seemingly, learners who are prepared to learn collaboratively build task-based collaboration schemas. They may be applied through analogical transfer when these collaborative groups must learn similar tasks (Gick & Holyoak, 1980). It may be reasonable to think that domain-generalizable knowledge for collaboration operates as intergroup guides that take advantage of transactional activities to better learn relatively new tasks.

Furthermore, the effectiveness of collaborative learning is affected by prior task knowledge (Retnowati et al., 2018; Zhang et al., 2015, 2016). Providing preliminary instruction to construct partially developed domain-specific knowledge before subsequent explicit instruction may produce higher performance in the retention and delayed tests than learning individually without such prior knowledge. Similarly, learning collaboratively with partial knowledge structures yields higher performance than collaborating among less knowledgeable learners. However, when individuals and collaborative groups with this prior knowledge are compared, the advantage of learning in collaborative groups only decreases the mental effort in the learning phase (i.e., due to the advantage distribution) and produces higher performance in the retention test. In the longer term (i.e., delayed test), the performance between collaborative groups and individuals is equal. However, if learners have not received preliminary instruction, learning in collaborative groups is more effective with higher performance than learning individually in the short- and long-term as indicated by the retention and delayed tests respectively.

5.1. Practical implications

This study has educational implications when the learning goal is to learn high-complexity problems, and when high performance needs to be sustained in the longer-term. First, if collaborative learning is used, learners should be provided preparation in learning in collaborative groups through practice on tasks previously learned in the same domain. Once learners have had a collaborative group experience, they will then be able to manage the collaborative cognitive load and transfer this experience to relatively new problems. Also, before giving explicit or full comprehensive instruction for learning to solve quite complex problems, novice collaborative group members should receive preliminary knowledge to guide subsequent acquisition. Instructors can begin instruction by providing guidance using worked examples to first stimulate individual long-term memory elaboration and then promote the construction of better schemas through collaborative learning.

However, if learners have prior task-specific knowledge, learning in collaborative groups may not be more beneficial than learning individually because collaborative groups experience more cognitive load during full guidance (i.e., learning phase) and an advantage in performance is not durable in the long term.

5.2. Limitations and future directions

Assuming that cognitive load may vary during learning (Kalyuga & Plass, 2018), it is important to develop ways of measuring it during collaboration activities. Making collaborative group activities explicit along with their respective cognitive loads is fundamental. For this, an in-depth analysis of the loads related to transactional activities is required concerning how group members process task information individually and amongst themselves and how learners support each other to overcome task-related difficulties. An evaluation of the impact of transactional activity patterns on performance and mental effort in individual long-term post-tests also is required.

Further, the subjective measurement of cognitive load may not be appropriate for collaborative learning (F. Kirschner, Paas, & Kirschner, 2011; Retnowati et al., 2016). Although the mental effort scale appears to be robust for individual conditions, it should be determined if it is valid and reliable for collaborative learning conditions. Other measures of cognitive load that account for the multiple sources and types of cognitive load in collaborative conditions may need to be constructed.

Another limitation of this study is that a pretest was not used. Although the tasks in the learning phase are not easily acquired without being part of a curricular program, students might acquire this knowledge outside the school context. Of course, our use of random allocation to groups should eliminate any systematic biases. A pretest would test whether this is the case.

This study is a first step to uncover the cognitive load factors associated with individual and collaborative learning considering the prior knowledge effect. Future studies should replicate this study to confirm these results and examine the effect of prior knowledge between individual learning, and collaborative learning with and without collaborative preparation. Also, tasks with higher and lower complexity should be used to investigate relations between prior knowledge and complexity.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2019.05.011.

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