# The Effect of the Prior Collaborative Experience on the Effectiveness and Efficiency of Collaborative Learning

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**Abstract:** This study investigates, from a cognitive load perspective, the effect of prior collaborative experience on the effectiveness and efficiency of collaborative learning. Performance, mental effort, and efficiency were measured during collaborative learning and in individual post-tests after one and seven days (i.e., retention and delayed retention test respectively). The results with 90 high school participants found that students who were members of experienced groups outperformed, invested less mental effort, and were more cognitively efficient than students in non-experienced groups in both tests. These results have important instructional implications for designing collaborative environments and provide support for the advantages of forming teams with relevant collaborative experiences before starting collaborative learning.

**Keywords:** collaborative learning, cognitive load theory, prior collaborative experience.

## Introduction

Collaborative learning is an extensively used instructional technique in educational settings. It is the process by which individuals interdependently interact in small groups to learn from solving academic problems (Gillies, 2016; Slavin, 2014). This instructional approach has been broadly studied from multiple disciplines and perspectives (Hmelo-Silver, Chinn, Chan, & O'Donnell, 2013; Hmelo-Silver & Chinn, 2015). Although there is research from different perspectives using different theories, the conditions under which collaborative learning is effective and efficient are still insufficiently understood (Kester & Paas, 2005; Kirschner, Paas, & Kirschner, 2009). Studying collaborative learning from a cognitive perspective (i.e., taking human cognitive architecture into account) will provide valuable insights and guidelines for designing effective and efficient collaborative learning environments. The current study shows that in this context, having prior collaborative learning experience is an important determining factor.

### Collaboration experience

Researchers have been concerned about the conditions under which collaborative groups are most effective. The literature presents multiple ways of designing learning environments based on collaboration (Gillies, 2016; Slavin, 2012). However, the availability of task-group skills has proven to be a critical factor in achieving better learning outcomes. (Delise, Allen Gorman, Brooks, Rentsch, & Steele-Johnson, 2010; Fuchs, Fuchs, Kazdan, & Allen, 1999; Johnson & Johnson, 2009; Webb, 2009).

Literature shows that experience with collaboration produces positive effects on performance with only a few instructional sessions and with benefits extending up to one year. Prichard, Stratford, and Bizo (2006), for example, trained groups in two 45-minute sessions delivered one week apart. They found that the groups that received this treatment and remained intact performed better than groups composed of reassigned members and untrained groups. They also found that groups with reassigned members outperformed untrained groups. Buchs, Gilles, Antonietti, and Butera (2015) gave a 10-minute instruction to groups on cooperative skills. They found that collaborative learning in dyads that received the instruction led to better learning outcomes compared to learning individually or collaboratively without the instruction.

As to long-term benefits, Prichard, Bizo, and Stratford (2006) tested whether the benefits of collaboration experience were maintained for two semesters. They compared three cohorts. In cohort 1, learners worked in groups during Semester 1 without training and in Semester 2 were reassigned to new groups. In cohort 2, groups received instruction on how to work collaboratively in Semester 1 and in Semester 2 group members were reassigned to new groups. Cohort 3 received guidance and their groups remained intact during both semesters. The results showed that the groups that were instructed on how to work collaboratively outperformed untrained groups. However, the guidance advantage of cohort 2 decreased significantly in Semester 2 while cohort 3 maintained its performance in both semesters. The researchers concluded that the benefits of knowing how to collaborate may be lost if groups are disbanded.

 

These and other research (Franke et al., 2015; Jordan & Métais, 1997; Yamarik, 2007) suggest that it is possible to instruct learners as to how to effectively collaborate in groups and thereby obtain immediate positive results compared to groups without this instruction. To understand the positive effects of prior collaborative learning experience one can look at the results from a cognitive perspective, namely, that collaborative skills may be a type of knowledge that can be acquired in long-term memory (LTM) and transferred to analogous domain-specific tasks (Kalyuga, 2009).

## Collaborative learning from a cognitive load perspective

Cognitive load theory (CLT) looks at how people learn considering their cognitive architecture (Sweller, Ayres, & Kalyuga, 2011). CLT is based on the premise that learning is limited by the spatiotemporal limitations of working memory (WM), namely that its capacity is very limited and that processing must occur within a very short period of time (Baddeley, 2011). A crucial factor here is the number of novel interactive elements of a task or learning material. If new information surpasses the WM capacity (overload), learning is poor. For this reason, the cognitive load of complex tasks (i.e., tasks with a large number of interacting elements) must be optimized through instructional manipulation. One way to reduce the cognitive load and promote better learning of complex tasks is to design appropriate collaborative environments taking advantage the primary knowledge associated with group communication (Paas & Sweller, 2012). Instead of processing all new information elements, each collaborator would receive a small, relevant information quantity to process and share with others. The collective distribution of information not only reduces the cognitive load of the task but also takes advantage of the biologically social way of learning (Paas & Sweller, 2012; Tomasello & Gonzalez-Cabrera, 2017).

Studying collaborative learning from a cognitive load perspective is gaining attention (F. Kirschner, Paas, & Kirschner, 2011; Paas & Sweller, 2012). An effect explaining the advantage of collaborative learning is the *collective WM effect* which holds that in collaborative learning, group members can make use of each other's WM resources by sharing the cognitive load imposed by a complex task (F. Kirschner et al., 2011). Because collaborative learning requires investing additional WM resources in transactional activities, (i.e., communication and coordination), the benefit of sharing information processing among collaborators should be larger than the load related to the transactional activities (F. Kirschner et al., 2011; F. Kirschner, Paas, Kirschner, & Janssen, 2011). Studies on the effect of (a) task complexity (i.e., low versus high complexity; (F. Kirschner et al., 2011; Kirschner, Paas, Kirschner, et al., 2011), (b) prior knowledge (i.e., novice versus knowledgeable learners; (Zhang, Kalyuga, Lee, & Lei, 2016; Zhang, Kalyuga, Lee, Lei, & Jiao, 2015), and (c) instructional strategies such as worked-out examples (WOEs) and the solution of conventional or partially structured problems (Retnowati, Ayres, & Sweller, 2010, 2016; Zhang, Ayres, & Chan, 2011) have generally found that collaborative learning produces better learning when task complexity is high, groups are composed of novices and advanced learners (i.e., heterogeneous groups), and problems are partially structured.

Until now, however, the possible advantage of having prior collaborative experience on relevant tasks has not been studied from a CLT perspective. Prior experience working together may have group members gain specific generalized knowledge related to collaborative skills. With respect to CLT, this means that experienced groups have appropriate collective knowledge structures in LTM (i.e., group schemata) that reduce the load when learning from comparable (i.e., the same or related domain) new complex tasks. These schemata would function as an group central executive that guide groups to better regulate themselves (Järvelä, Järvenoja, Malmberg, & Hadwin, 2013; Kalyuga, 2015), get involved in joint cognitive activities related to the learning tasks (Webb, 2009), and avoid cognitive and emotional non-relevant interactions. When necessary, this collective knowledge can be recovered from LTM by activating retrieval cues that facilitate analogical transfer (Gick & Holyoak, 1983; Kalyuga, 2013). If collaborative learning tasks are highly demanding, relevant prior collaborative experience could, therefore, facilitate acquiring content knowledge (i.e., the subject matter of the learning task) because collaborators can focus their collective WM resources on relevant task-related transactional activities. In sum, groups with relevant previous collaborative experience would learn better and be more cognitively efficient than groups that have not had appropriate experience or received guidance on how to collaborate.

## The present study

This study looks at whether prior collaborative experience in relevant tasks improves the effectiveness and efficiency of the process and outcomes of collaborative learning in complex analog tasks. We expected that experienced groups would perform better (H1), invest less mental effort (H2), and be more cognitively efficient (H3) than non-experienced groups.

# Methods

## Participants

The study was conducted with 90 Ecuadorian 10th students grade from a private high school (see Table 1; 46 males (51.1%); 44 females (48.9%), $M_{age}$ = 13.86 years 13.86 years ($SD$ = .71). The choice for this sample is based upon the fact that collaborative learning in Ecuador is often introduced at this level as an approach to study and learning. To control the effect of task prior knowledge (Kalyuga, Ayres, Chandler, & Sweller, 2003), participants received a knowledge test before the learning tasks that resulted in the exclusion of three learners from the learning phase and the following ones. Participants were notified of the study, gave informed consent, were informed that they would not receive academic compensation for participation, and were randomly assigned to the two learning conditions.

Table 1: Participants for each study phase

| Learning Conditions | *N* |
|---|---|
| Training Phase | 90 |
| Experienced Groups | 45 |
| Non-Experienced Groups | 45 |
| Learning Phase | 87 |
| Experienced Groups | 45 |
| Non-Experienced Groups | 42 |
| Retention Test Phase | 86 |
| Experienced Groups | 44 |
| Non-Experienced Groups | 42 |
| Delayed Test Phase | 85 |
| Experienced Groups | 45 |
| Non-Experienced Groups | 40 |

## Design and procedure

A one-way (experienced vs. non-experienced group) factorial design was used. The study was conducted in four phases with 45-minute sessions: training, learning, retention test, and delayed test. Two instructors and the experimenter guided participants by reading guidelines aloud before each phase. Instructors were informed in advance about the procedure and were supervised by the experimenter to ensure the fidelity. A computer with a digital clock was present to show the number of minutes allotted to each task.

### Training phase

In this phase, groups were formed and instructed on how to effectively collaborate on a domain-specific task in mathematics (see Materials). It began in the second week of the new school term after the school vacation, ensuring that participants had no prior collaboration experience in the previous two months. The 90 participants were randomly assigned to two conditions: 45 worked in 3-person groups (i.e., experienced group condition) and 45 worked individually. All participants worked on the same training tasks during four sessions, two sessions per day, over one week. The first tasks had no time constraints. The last two tasks of the second session onward had to be solved in 10 min. While resolving the tasks, learners from the experienced group condition were instructed on how to interact and coordinate amongst themselves to share their items and maintain in their WM the partial calculations to find the correct solution. Learners in the individual condition worked on the tasks by themselves. At the end of each session, participants received the correct answers and were asked to plan (5 min) how they might work better.

### Learning phase

This phase evaluated the effect of team formation on the learning process. It was conducted in one session (45 min) after the training phase. Participants received a prior knowledge pre-test consisting of three items relating to economics (see Materials): total fixed cost, unit variable cost, and price (see Table 2). They were asked to individually calculate the break-even point. Then, students that worked individually were randomly distributed into 14 3-persons groups (i.e., the non-experienced group condition). The experienced groups remained intact. All groups worked on three tasks for 21 min (i.e., 7 min per task). Groups were told by instructors to focus on the topic – to avoid extraneous conversations – and writing while performing the calculation was not permitted – to avoid cognitive off-loading through external representations (Van Bruggen, Kirschner, & Jochems, 2002). The instructors allowed only one group member to write down the answer for each problem and all groups members to write down the amount of mental effort invested in each problem. If a group solved the problem before the allotted time, they could check again if the problem was well resolved and/or had to wait before beginning on the next problem.

### Retention and delayed test phases
These final two phases evaluated the effectiveness and efficiency of collaborative learning outcomes. They were conducted one and seven days after the learning phase, respectively. Participants were required to individually solve three problems in 30 min (i.e., 10 min per problem). Participants recorded the amount of mental effort invested in each problem (see Measurements). For these phases, writing down calculations was permitted.

## Materials
Materials used were in the domain of mathematics and the analogous domain of economics. Solving quadratic equations by factoring were utilized in the group training phase and break-even point calculation problems in economics in the learning, retention test, and delayed test phases. All materials were paper-based.

### Training phase
In Session 1, participants received a two-part booklet. The first part gave a general introduction to quadratic equations with two WOEs using the factoring method; "a step-by-step demonstration of how to perform a task or how to solve a problem" (Clark, Nguyen, & Sweller, 2006, p. 190). The second part presented the generalized-domain group knowledge via rules on how to collaboratively solve the equations, followed by a WOE demonstrating how each member should apply them, and a conventional task with the correct answer. All participants received the same instruction. In Session 2, participants again received the collaborative learning rules, two conventional problems with the correct answer and a conventional problem without the correct answer. In Sessions 3 and 4, groups and individuals received three conventional quadratic equation problems without a correct answer. Each group member received 1/3 of the information elements, which means that they were relevant, but insufficient to solve the problem.

### Learning phase
Calculating a break-even point in economics is a task which is analogous to solving quadratic equations because they display similar characteristics such as combining multiple numerical values, calculating partial step answers, holding them in WM, finding a unique correct answer, and so forth. Participants received a booklet introducing relevant concepts with two WOEs, prompt questions, three learning tasks, and a piece of paper with examples of costs and the break-even point in unit's formula. A WOE showed how to calculate the break-even point in units and sales with a profit margin. The other was similar but without the profit margin. The WOEs had a 7-step procedure (see Table 2). Some of the prompt questions were: a) What were the break-even points? b) What were the seven steps to calculate the break-even points? c) What was the difference between the break-even points in units and sales? d) How did you calculate the contribution? and so forth.

Table 2: Steps to calculate the break-even point

| *Steps to solve the problem* | *Example of calculations* | *Interacting elements* | *Elements in WM* |
|---|---|---|---|
| 1. Recognize cost items | Nine items of the problem<br>155, 63, 82, 50, 41, 108, 71, 119, 52 | 9 | |
| 2. Total variable cost | $VC_1 + VC_2 + VC_3 = TVC$<br>155 + 63 + 82 = 300 | 7 | 300 |
| 3. Variable cost per unit | TVC ÷ amount produced = CU<br>300 ÷ 50 = 6 | 5 | 300, 6 |
| 4. Contribution | Price – CU = CM<br>41 – 6 = 35 | 5 | 6, 35 |
| 5. Total fixed cost | $FC_1 + FC_2 + FC_3$ + profit margin = TFC<br>108 + 71 + 119 + 52 = 350 | 9 | 35, 350 |
| 6. Break-even point in units | TFC ÷ CM = BPU<br>350 ÷ 35 = 10 | 5 | 35, 350, 10 |
| 7. Break-even point in sales | BPU × price = BPS<br>10 × 41 = 410 | 5 | 10, 410 |

*Note*. CV = variable cost; FC = fixed cost; TVC = total variable cost; CU = variable cost per unit; CM = contribution margin; TFC = total fixed cost; BPU = break-even point in units; BPS = break-even point in sales.

To make sure the complexity of the tasks (i.e., the element interactivity level) would be sufficient, teachers of economics were asked to check whether the tasks were complex enough for novices. Furthermore, the Sweller and Chandler method (1994) was used to determine the task complexity, consisting of counting the number of interacting elements to solve the tasks. As shown in Table 2, the procedure had seven steps and nine items. The items represented the values to calculate the break-even point (i.e., three fixed costs, three variable costs, a price, a profit margin, and the number of produced things). This amounted to a total of 45 (including mathematical signs). For each step, a partial result had to be calculated and had to be held in WM (Column 4) and then integrated with another partial result. Finally, not allowing students to write down the calculations but having them keep the information in WM increased the task complexity. Based upon these analyses, it can be claimed that the tasks were complex.

#### Retention and the delayed test phases

Six complex problems similar to the learning tasks were designed, but cost names were varied for new business situations. These tasks had an equal level of complexity (i.e., number of information elements) to the learning tasks. Participants received worksheets with three tasks on the day after the learning tasks (i.e., retention test), and the other three seven days after the learning tasks (i.e., delayed test). Each problem included a table with seven numbered rows to write down the calculations for each step of the task's solution.

### Measurement

#### Performance

Performance was measured in the learning, retention test, and delayed test phases. The maximum score for all the three learning tasks was 3; 1 per task, if correct and 0 if incorrect. For each of the three retention test tasks (i.e., retention test phase), 7 points could be awarded. These points were based on the 7 calculations required to determine the break-even point. A correct step's calculation received 1 point and an incorrect 0. This resulted in a maximum score of 21 points and a minimum of 0. If a step was partially correct (e.g., if only two of the three variable variables were recognized in step 2), a proportional score was given. The same scores system was applied to the delayed test phase. All scores were transformed into proportions.

#### Cognitive load

Cognitive load was measured after each task of the learning, retention and delayed test phases with the subjective 9-point mental effort rating scale (Paas, 1992). Participants were asked to rate how much effort it took for them to solve the problems on a scale ranging from very, very low effort (1) to very, very high effort (9). This scale has been found to be sensitive to changes in task complexity, to be non-intrusive, valid, and reliable (Van Gog & Paas, 2008).

#### Cognitive efficiency

Cognitive efficiency was calculated by standardizing each of the participant's scores for task performance and the mental effort (Paas & Van Merriënboer, 1993). For each participant, z-scores were calculated for effort (R) and performance (P) to obtain the cognitive efficiency (E) using the formula: $E = [(P - R)/2^{1/2}]$. A high efficiency denotes relatively high performance combined with relatively low mental effort. By contrast, low efficiency denotes relatively low performance combined with relatively high mental effort.

## Results

Data were analyzed with a one-way (experienced vs. non-experienced groups) analyses of variance (ANOVAs). Dependent variables were performance, mental effort, and efficiency, which were measured for the learning, retention, and delayed phases (see Table 3 for descriptive statistics). A significance level of .05 and casewise deletion were used to analyze data. Partial eta-squared was computed as a measurement of the effect size, with values of .01, .06 and .14, corresponding respectively to small, medium and large effects (Cohen, 1988).

### Learning phase

Concerning performance, ANOVA revealed no significant difference between experienced and non-experienced groups, $F(1, 85) = .024$, MSE = .742, *ns*. For mental effort, ANOVA revealed no significant difference between experienced and non-experienced groups, $F(1, 85) = .796$, MSE = 1.709, *ns*. For cognitive efficiency, ANOVA also revealed no significant difference between experienced and non-experienced groups, $F(1, 85) = .367$, MSE = 1.265, *ns*.

Table 3. Mean and standard deviations for dependent variables

| | Learning phase | | | | Retention test phase | | | | Delayed test phase | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Experienced | | Non-experienced | | Experienced | | Non-experienced | | Experienced | | Non-experienced | |
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| Performance (0-1)[a] | .60 | .65 | .57 | 1.06 | .57 | .19 | .47 | .19 | .49 | .21 | .40 | .18 |
| Mental effort (1-9) | 6.84 | 1.27 | 7.09 | 1.35 | 5.99 | 1.55 | 7.24 | 1.67 | 6.37 | 1.51 | 7.04 | 1.55 |
| Cognitive efficiency[b] | .04 | .76 | −.10 | 1.42 | .43 | 1.11 | −.47 | 1.25 | .30 | 1.23 | −.32 | 1.03 |

[a] Proportions of the correct answers on the retention test tasks.
[b] Based on the z-scores of the mental effort and performance scores.

### Retention test phase
For performance, ANOVA revealed a significant difference between experienced and non-experienced groups, $F(1, 84) = 6.754$, MSE = .035, $p = .001$, $\eta_p^2 = .074$. For mental effort, ANOVA also revealed a significant difference between experienced and non-experienced groups, $F(1, 84) = 12.890$, MSE = 2.587, $p = .001$, $\eta_p^2 = .133$. For cognitive efficiency, similarly ANOVA revealed a significant difference between experienced and non-experienced groups, $F(1, 84) = 12.479$, MSE = 1.391, $p = .001$, $\eta_p^2 = .129$.

### Delayed test phase
Regarding performance, ANOVA revealed a significant difference between experienced and non-experienced groups, $F(1, 83) = 4.557$, MSE = .039, $p = .036$, $\eta_p^2 = .052$. For mental effort, ANOVA showed a significant difference between experienced and non-experienced groups, $F(1, 83) = 4.095$, MSE = 2.330, $p = .046$, $\eta_p^2 = .047$. For cognitive efficiency, similarly ANOVA found a significant difference between experienced and non-experienced groups, $F(1, 83) = 6.176$, MSE = 1.297, $p = .015$, $\eta_p^2 = .069$.

## Discussion
This study focused on the learning effectiveness and efficiency of groups with prior collaborative experience. We expected that experienced groups would perform better (H1), invest less mental effort (H2), and be more cognitively efficient (H3) than non-experienced groups. The results confirm the three hypotheses for retention and delayed retention phases. Our data suggest that groups that received guidance and therefore had knowledge schemata about how to work together on analogous tasks took advantage of their inter-individual activities to learn better. The cognitive load associated with transactional activities (F. Kirschner et al., 2011) can be substantially reduced through the use of such group schemata so that collective WM resources can be focused on productive collective activities to construct better LTM mental representations on the content matter.

The superior effectiveness and efficiency of the experienced groups confirm evidence of the effects of training obtained by Prichard, Stratford, et al. (2006) and Buchs et al. (2015). In addition, this research contributes to the emerging concept of generalizable domain knowledge of CLT at group level (Kalyuga, 2009, 2013, 2015). We suggest that collaborative experience in tasks relevant for later learning is a type of generalizable knowledge that can be transferred to relatively new (i.e., analogous) learning situations. We can suggest that these task-based collaborative knowledge structures function as shared regulatory guides (Järvelä, Järvenoja, & Näykki, 2013; Kalyuga, 2015) that orient the interaction amongst collaborators. Consequently, experienced groups are more able to reduce WM resources associated with unprofitable interactions and putting more cognitive effort on learning from each other while solving the problem (i.e., germane or productive interactions).

This study has important instructional implications. If a task is complex, teachers should form groups composed of members who have previously worked together on similar tasks. Or, if this is not possible, implement a training phase like the one used in this study so that group skills can be acquired in a relatively short time. Important aspects of the preparation are: give specific instruction on how to work together using WOEs, provide incomplete and conventional tasks to apply and test collaborative schemata, use collaborative tasks in a related field, and encourage group members to focus their interactions on the most demanding parts of the task. Once the collaborative skills based on specific tasks have been acquired, groups can then be confronted with new complex tasks in the same or related domain.

Finally, more research is needed to overcome some limitations of this study. Because no evidence was found for our hypotheses in the collaborative learning phase, it is crucial to better understand the collaborative learning process itself from a CLT perspective. Doing this requires an in-depth analysis of which are those group cognitive activities associated with information processing, and how learners support each other to manage task-related difficulties.

All in all, CLT adds a dimension to our understanding of how to improve the effectiveness and efficiency of collaborative learning.

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