12th International Conference on Intelligent Tutoring Systems
Honolulu, Hawaii, June 5-9, 2014

Using an Intelligent Tutoring System to Support Collaborative as well as Individual Learning

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Abstract. Collaborative learning has been shown to be beneficial for older students, but there has not been much research to show if these results transfer to elementary school students. In addition, collaborative and individual modes of instruction may be better for acquiring different types of knowledge. Collaborative Intelligent Tutoring Systems (ITS) provide a platform that may be able to provide both the cognitive and collaborative support that students need. This paper presents a study comparing collaborative and individual methods while receiving instruction on either procedural or conceptual knowledge. The collaborative groups had the same learning gains as the individual groups in both the procedural and conceptual learning conditions but were able to do so with fewer problems. This work indicates that by embedding collaboration scripts in ITSs, collaborative learning can be an effective instructional method even with young children.

Keywords: Problem solving, collaborative learning, intelligent tutoring system

1 Introduction

While collaborative learning has been shown to be beneficial for both face-to-face and Computer Supported Collaborative Learning (CSCL) [9], [14], collaborative learning often puts challenges on students and teachers that make it hard to implement in the classroom. The challenges teachers face include preparing materials, teaching the students collaboration skills, and learning how to manage small groups [3]. For students, fruitful collaboration does not happen spontaneously, and collaboration scripts are used to support students in their learning [6]. It is important for a script to match the learning goals of the activity and to provide enough support for the students without over-scripting. Collaboration can be supported through different features such as roles, cognitive group awareness, and the distribution of information. The challenges faced by both the students and teachers can make the use of collaboration daunting. Some prior research has indicated that Intelligent Tutoring Systems (ITSs) can be a practical way of addressing the challenges of using collaboration in the classroom. Most CSCL environments are missing the cognitive support that can be beneficial to student learning. An ITS can provide the cognitive support (i.e. step-by-step guidance and hint features) that a student needs for collaboration to be successful [18], but does not provide support for effective collaboration. The current research investigates if embedding a collaboration script into an ITS so it has both the collaborative and cognitive support can help a student to learn successfully.

Even though collaborative learning has been shown to be successful in some instances, few studies have investigated whether CSCL can have a positive impact on learning with young children. The implementation and support of collaboration in the classroom is particularly difficult for students in elementary school and may explain why there is less research with this age group. An important question then is if collaborative learning can be an effective instructional method to use with elementary school students and if it would lead to similar learning gains as students working individually. Some studies have shown successful use of collaboration with elementary school students as well, but have either compared the use of a CSCL setting to face-to-face collaborative learning (i.e., not supported by computers) without comparing it to individual learning or have focused on interventions that mix individual and collaborative learning tasks without looking at each separately [1], [8], [16]. Although this research has shown positive impacts of young children working in small groups and with computers, it is still unknown how the use of a CSCL environment impacts the learning outcomes of young children compared to learning individually. This paper aims to address this question through an ITS designed specifically to support collaborative learning of children in elementary school. ITSs have been shown to have positive impacts on students in this age group when working individually to learn fractions [12]. We now extend this research by testing whether a tutor that supports collaboration can be effective for learning fractions by elementary school students.

Although most prior work on ITSs has focused on individual learning, there has been some work on combining ITSs with collaborative learning that has shown promise for supporting learning with high school students [17]. Walker et al. found that students working with an ITS redesigned to support collaboration (specifically, peer tutoring) had learning gains at least equivalent to those working individually.

In creating a collaborative tutor, it may be important to consider the possibility that individual and collaborative learning activities may be better for acquiring different types of knowledge, such as conceptual and procedural knowledge [10]. Conceptual knowledge is the implicit and explicit understanding of the principles in a domain and how they are interrelated [13]. Procedural knowledge is the ability to be able to perform the steps and actions in sequence to solve a problem [13]. Mullins, Rummel, and Spada found that with 9^{th} graders doing algebra, students who worked collaboratively on conceptual tasks outperformed those who worked individually and students who worked individually on procedural tasks outperformed those who worked collaboratively [10]. Again, this study was implemented with older students and the question still remains if the same difference will be seen with elementary school students.

Why would it be better to acquire different types of knowledge through different instructional methods? Following the Knowledge-Learning Instruction (KLI) framework, instruction should be designed for both the domain and for the type of knowledge component to be learned [5]. Simpler instructional methods tend to be associated with simpler knowledge components, more complex methods with more complex knowledge components. Thus, collaboration, a more complex instructional method, would be better for more complex knowledge components, where elaboration and a deeper understanding is needed, such as those in conceptual knowledge. More specifically, collaborative learning may be successful because the students give and receive explanations and construct knowledge through their discussions [4]. On the other hand, individual learning would be more geared towards procedural learning where practice and repetition are more important for developing fluency.

In our study, we address the feasibility of using a collaborative ITS with elementary school students learning fractions. We hypothesize that students working collaboratively will show learning gains on both procedural and conceptual fractions tasks. Also, we hypothesize that on conceptual tasks, students working collaboratively will have stronger learning gains than students working individually. By contrast, for students doing procedural tasks, we hypothesize that those working individually will have stronger learning gains than those working collaboratively. These hypotheses are consistent with both the KLI framework and the Mullins et al. findings.

2 Methods

2.1 Tutor Design

Informed by our prior work on the Fractions Tutor [12], we developed a new ITS for a challenging topic in fractions, learning equivalent fractions. Specifically, we built two parallel versions of this tutor for use in our study, one with embedded collaboration scripts and one for individual learning. Both versions had procedural and conceptual problem sets. Both were built with CTAT, which we extended to support collaborative tutors [11]. The collaborative ITS combines the cognitive support normally provided by an ITS (step-level guidance for problem solving) with embedded collaborative scripts for each tutor problem. The collaboration is supported through the use of a shared problem view, roles, cognitive group awareness, and unique information. First, the collaborative tutors support synchronous, networked collaboration, in which collaborating students sit at their own computer and have a shared (though differentiated) view of the problem state. They can discuss the activity through audio chat.

Second, the embedded scripts define roles to distribute the activities between the students. The roles provide guidance to the students about what they should be doing to interact with their partner and help to scaffold this interaction. Students were assigned to either a helper role or a problem solver role for each task in a problem. The students were informed of their role assignment through the use of icons displayed on the interface (see Figure 1). An “ask” icon next to a problem step signaled to the student that they were in the helper role and responsible for asking questions and making sure both they and their partner understood the answer. A “do” icon next to a component meant the student was in the problem solver role and responsible for carrying out the step to move the problem solution forward (Figure 1).

A third collaborative support feature we used in the collaborative problem sets is cognitive group awareness. Cognitive group awareness means that group members

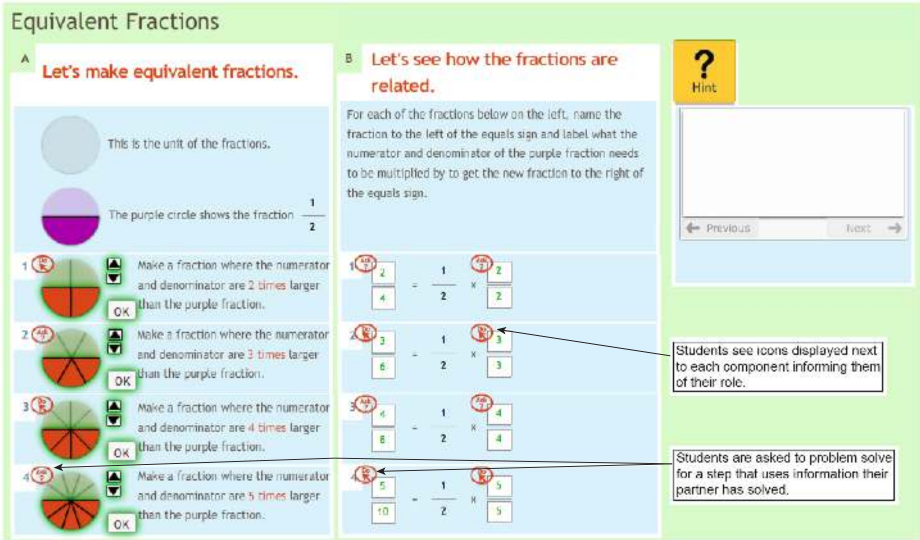

Fig. 1. A collaborative procedural problem: multiplying to make equivalent fractions.

have information about other group members' knowledge, information, or opinions and has been shown to be effective for the collaboration process [7]. We implemented cognitive group awareness by a design pattern in which the collaborative tutor poses a question to both students and asks each student to answer independently first without being tutored (bottom of Figure 2). After both students answer the question independently, the tutor shows them each other's answers and gives them the opportunity to answer the question as a group, which is tutored. This activity allowed each student an opportunity to express an opinion and gave each dyad an opportunity to discuss and explain their answer choices, especially important when they disagreed.

The last collaborative support feature is the use of unique information to create a sense of individual accountability, a popular feature in scripts such as the jigsaw [2]. Individual accountability means that each group member takes responsibility for the group reaching its goal [14]. By providing each student with information that their partner does not have and that is needed to complete the problem, both students have a stake in completing the problem. In our problem sets, unique information was implemented by providing one member of the dyad with some information the other student did not see. The student would know they had unique information because there would be a share icon next to the information. The other student would need this information to complete a step of the problem and would see a listen icon to know there was some information they needed to get from their partner.

To test our experimental hypotheses, two problem sets were created for both the collaborative and the individual ITSs. One set focused on procedural knowledge of equivalent fractions while the other set focused on conceptual knowledge of equivalent fractions. The procedural problem set has four problem types, with four problems each, which focus on finding equivalent fractions or determining whether fractions are equivalent, either by finding the common factors and reducing the fraction or by

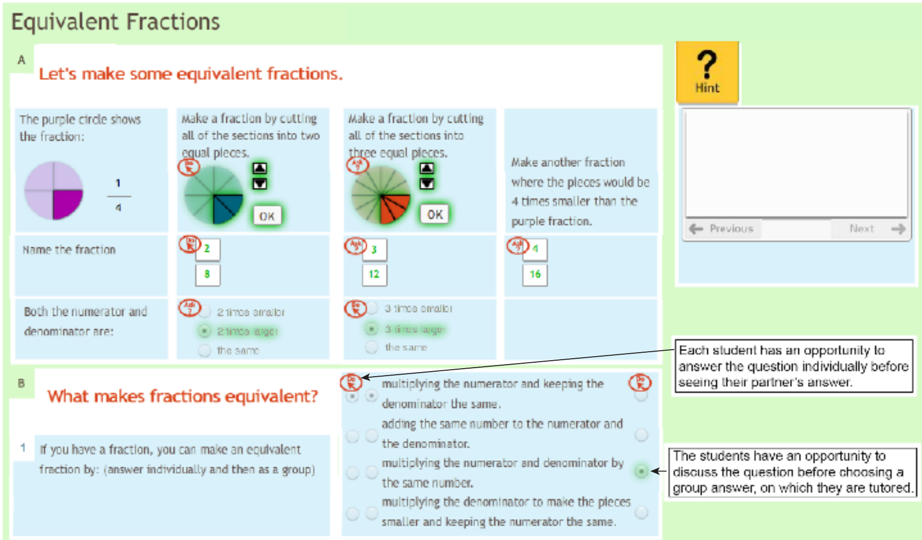

Fig. 2. Example of a collaborative conceptual problem: creating equivalent fractions to find the pattern in the fractions.

multiplying the numerator and denominator by the same number (see Figure 1). Each of the problem types focused on the steps needed to complete that procedure, without addressing conceptual questions about why the procedure works. The conceptual problem set also has four different problem types and four problems of each type. Two of the problem types provide the students with two stories about whether given fractions are equivalent that they need to compare and contrast (one story is correct and one story focuses on a misconception) or by providing the students with one story that focuses on a misconception that students need to address. The other two problem types focus on the definition of equivalent fractions by either having the students construct equivalent fractions to find a pattern in the fractions or by having students manipulate the denominators and numerators of the fractions independently to see how they relate (see Figure 2). For both problem types, students then induce a definition of what it means for fractions to be equivalent.

2.2 Experimental Design and Procedure

To test the hypotheses stated above, we conducted a study with 84 4th and 5th grade students from two US elementary schools in the same school district. The students came from a total of six classrooms. The experiment was a "pull-out" design, where the student left their normal instruction during the school day to participate in the study. (We did so we could collect eye tracking data, which are not reported here.) All students worked with the fractions ITS designed for this study and described above. Each teacher paired the students participating in the study based on students who would work well together and had similar math abilities. These pairs were then randomly assigned to one of four conditions: collaborative conceptual, collaborative procedural, individual conceptual, and individual procedural. Twice as many students were assigned to the collaborative conditions as to the individual conditions.

Before participating in the pull-out session, the students had two whole class sessions during which they worked individually with the Fractions Tutor during their normal class period (on fractions topics other than equivalence). This allowed the students to become acclimated with the tutor before the experiment began. During the experiment, the students participated in a 25-minute pretest the morning of their participation. Throughout the day, the pairs of students participated in the pull-out session. Each such session lasted for one hour where during this time, they received 45 minutes of instruction dependent on their condition. The next school day, the students participated in a 25-minute posttest in the morning. The study spanned a total of four weeks. After the end of the study, the students again had two whole class sessions where they again worked independently on the Fractions Tutor.

2.3 Pre and Posttests

We assessed students' knowledge at two different times using two equivalent test forms in counterbalanced fashion. The tests targeted both conceptual and procedural knowledge types. Each test had 11 questions, five procedural and six conceptual. Each question either received a 1 when all parts were correct or a 0 otherwise. The test items were isomorphic to the items used in the practice problems.

3 Results

Table 1. Total correct: means (standard deviation) for conceptual and procedural knowledge at pretest, posttest, Min. score is 0, and max. score is 5 for procedural and 6 for conceptual.

			pretest	posttest
Conceptual Condition	Individual Condition	Conceptual Problems	2.00 (1.63)	2.54 (1.56)
		Procedural Problems	0.46 (0.66)	0.85 (1.21)
	Collaborative Condition	Conceptual Problems	2.04 (1.32)	2.54 (1.20)
		Procedural Problems	0.50 (0.75)	0.82 (0.82)
Procedural Condition	Individual Condition	Conceptual Problems	1.50 (0.76)	1.64 (1.28)
		Procedural Problems	0.50 (0.86)	0.64 (1.08)
	Collaborative Condition	Conceptual Problems	2.08 (1.67)	2.58 (1.42)
		Procedural Problems	0.92 (1.16)	0.92 (1.16)

Because the procedural and conceptual tutor problems were fundamentally different, each of these conditions was treated separately and the collaborative and individual conditions were not compared across problem types. Three students were excluded from the analysis because experimenter error, leaving 81 students. We analyzed the data by individual so we could evaluate each student's learning gain. To test our hypothesis that, on tutor activities targeting conceptual knowledge, students working collaboratively have higher learning gains than students working individually, we conducted two repeated-measures ANOVAs, one for procedural test items and one for conceptual items, with condition (collaborative or individual) as a between-subjects factor and test-time (pretest and posttest) as repeated measure. For the conceptual test items, there is a significant pre/post difference, $F\ (1, 39) = 4.23$, $p = .046$, no main effect of condition, $F\ (1,39) = .002$, $p = .966$, and no interaction, $F\ (1, 39) = .006$, $p = .940$. For the procedural test items, there is a marginal pre/post difference, $F\ (1, 39) = 4.00$, $p = .053$, no main effect of condition, $F\ (1, 39) = .001$, $p = .976$, and no interaction, $F\ (1, 39) = .032$, $p = .859$. There were significant learning gains for both the collaborative and individual condition and no difference in gains between conditions.

To evaluate our hypothesis that students working individually on tutor problems targeting procedural knowledge have higher learning gains than students working collaboratively, we conducted two repeated-measures ANOVA (for procedural test items and conceptual test items, respectively) with condition (collaborative or individual) as a between-subjects factor and test-time (pretest and posttest) as repeated measure. For the conceptual test items, there is no effect of pre/post, $F\ (1, 38) = 2.10$, $p = .16$, a marginal effect of condition, $F\ (1, 38) = 3.44$, $p = .071$ with the collaborative group higher, and no interaction $F\ (1, 38) = .65$, $p = .426$. For the procedural test items, there is no effect of pre/post, $F\ (1, 38) = .22$, $p = .64$, no main effect of condition, $F\ (1, 38) = 1.12$, $p = .297$, nor an interaction between condition and pre/post, $F\ (1, 38) = .22$, $p = .64$. There was no learning gain difference between the collaborative and individual conditions. The conditional difference reflects the fact that the students in the individual procedural group started lower at pretest and remained lower at posttest. We also analyzed learning curves derived from the tutor logs for evidence of learning during tutor use. Specifically, we looked at the slope coefficient in the AFM regression equation (see Figure 3), a standard way of analyzing tutor log data [15]. Averaged across knowledge components, the slope was 0.27 for the conceptual conditions and 0.15 for the procedural conditions. For the conceptual conditions, 81% of the learning curves has a slope of 0.05 or higher (a rule of thumb threshold value for a slope to represent effective learning) and for the procedural conditions, 60% of the learning curves had a slope above 0.05.

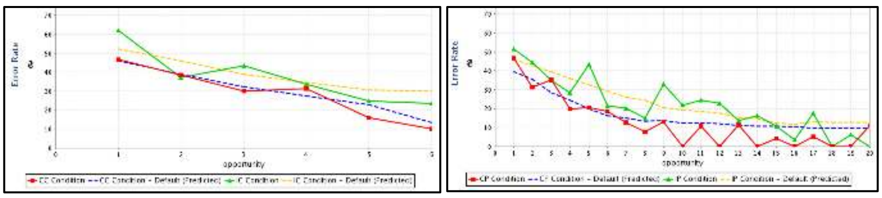

Fig. 3. Learning curves for conditions targeting conceptual (left) and procedural (right) knowledge. The learning curves are averaged across knowledge components encountered in the respective tutor problem sets. The red and blue lines represent the actual and AFM-predicted values for the collaborative conditions; the green and yellow lines for the individual conditions.

We conducted two t-tests (for each procedural/conceptual instructional condition) with collaborative/individual as the condition to see if there was a difference in the number of problems each student completed. For the procedural instructional condition, there is a significant difference, t (38) = 2.65, p = .012, with students working collaboratively doing fewer problems than students working individually by about 2.5 problems. For the conceptual instruction condition, there is a significant difference, t (39) =3.61, p = .001, again with students working collaboratively doing fewer problems than students working individually by about 3.5 problems.

4 Discussion and Conclusion

We hypothesized that elementary school students working collaboratively with a tutor designed to support collaboration would have learning gains from pretest to posttest. The hypothesis was confirmed; the students in the collaborative conceptual condition had learning gains comparable to those in the individual conceptual condition. In the procedural instructional condition, neither the collaborative nor individual conditions saw any learning gains. Thus, collaborative instruction might be as effective for elementary school students as individual instruction, although it appears to be more suitable for activities aimed at acquisition of conceptual knowledge. Collaborative learning activities may have the added benefit that they help students develop social skills and learn to work together.

While students in the collaborative condition saw fewer problems compared to their counterparts in the individual condition, they still had the same learning gains as the students in the individual conditions. This is consistent with other findings in CSCL [17]. This means that when authoring tutors, if collaborative tutors are used, fewer problems need to be developed to facilitate learning. However, we controlled for time and if we had controlled for number of problems, students in the individual condition may have learned as much as the students in the collaborative condition but in less time.

While we had hypothesized that the individual condition would yield greater learning gains than the collaborative condition for activities geared towards acquiring procedural knowledge and that the reverse would hold for activities geared towards acquiring conceptual knowledge, we did not find these differences. We may not have found these differences because the instructional period was relatively short. On average the students in the collaborative conceptual condition completed 7 problems. Because the problem types were interleaved and not all knowledge components were present in each problem type, the students did not always get to practice each knowledge component sufficiently. For the collaborative condition, out of the 16 knowledge components targeted in the conceptual problems, 9 of the knowledge components saw (on average, per student) fewer than 5 opportunities to practice a knowledge component. However, the students in the individual condition completed 12 problems on average and had at least 5 opportunities for all 16 knowledge components. By lengthening the practice time with the tutor, such as using the tutor for consecutive days in the classroom, the students would have more time with the tutor and would get more practice. This would help the students to get more practice with the individual knowledge components.

A second explanation for the fact that the hypothesized differences between the conditions were not confirmed may be that the collaborative learning condition was more novel and perhaps more demanding for students. Put differently, students may need more practice with the instructional method of collaborative learning. Especially given that the number of skill opportunities was low, one might expect to see better performance on the posttest. Other studies have also shown that the introduction of new learning strategies can initially lead to worse learning [19]. These initial performance losses may initially mask the success of a new learning strategy.

The fact that there were no learning gains in the procedural conditions may be due to the fact that the procedural problems may have been too difficult for the students. We also saw that overall for all conditions, the average number of problems solved correctly for the procedural problem types on either the pretest or the posttest was below one out of five (see Table 1). The learning curves for the individual knowledge components do show signs of learning during the instructional session, with an averaged slope across knowledge components of 0.15, well above the 0.05 threshold. Though the learning curves show that students start at an error rate above 50%, they also show clear signs of improvement. Because many of the procedural problems are multistep, the tests may need to be more fine-tuned to the specific knowledge components being learned instead of a cumulative approach of getting the entire problem correct. To be able to differentiate between the procedural and conceptual knowledge, more work will need to be done to develop and test tutors that can target this knowledge.

The study presented in this paper extends ITSs to include support for collaborative learning activities. We have showed that collaborative ITSs are a feasible instructional tool to use with elementary school students, with learning gains equivalent to those of students working independently with ITSs. The students in the collaborative condition also expressed enjoyment in working with a partner to solve problems. To the best of our knowledge, our study is the first showing significant learning gains with elementary school students working with collaborative ITSs. The use of collaborative ITS shows initial promise with elementary school students.

Acknowledgments. We thank the Cognitive Tutor Authoring Tools team, Amos Glenn, and Ryan Carlson for their help. This work was supported by Graduate Training Grant # R305B090023 and by Award # R305A120734 both from the US Department of Education (IES).

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