Diagram Interaction during Intelligent Tutoring in Geometry: Support for Knowledge Retention and Deep Transfer

Kirsten R. Butcher (kbutcher@pitt.edu)
Learning Research & Development Center, University of Pittsburgh, 3939 O'Hara Street
Pittsburgh, PA 15260 USA

Vincent Aleven (aleven@cs.cmu.edu)
Human-Computer Interaction Institute, Carnegie Mellon University, 5000 Forbes Avenue
Pittsburgh, PA 15213 USA

Abstract

Prior research has shown that skilled problem solvers often demonstrate meaningful links between relevant visual and verbal knowledge components, but little is known about how to support novice learners in connecting visual and verbal information during learning or whether such support will improve learning outcomes. This work explored two methods to support meaningful connections between visual and verbal information in an intelligent tutor for geometry: 1) student interaction with diagrams during problem solving, and 2) student explanations that connected diagram features to geometry rules at each problem-solving step. Research was conducted in 10th grade classrooms using an experimental version of the Geometry Cognitive Tutor. Results demonstrated that interaction with diagrams promoted long-term retention of problem-solving skills and supported performance on transfer tasks; diagram-rule explanations did not significantly influence learning. Findings suggest that student focus on relevant visual information should be carefully integrated into problem-solving practice to support deep learning.

Keywords: visual interaction; diagrams; geometry; learning; transfer; retention; intelligent tutoring

Visual Representations in Skilled Performance

Existing research has found that experts use visual representations in rich and interconnected ways during skilled problem solving. Stylianou (2002) studied the problem-solving processes of professional mathematicians and noted that mathematicians used diagrams extensively to inform their analysis of the problem, their selection of subgoals, and their eventual solutions. During problem solving, mathematicians iteratively searched diagrams that they had generated or modified, using visual features to identify relevant information and to cue useful approaches.

Stylianou's (2002) results compliment previous research showing that expert problem solving demonstrates close connections between visual representations and existing knowledge. Koedinger and Anderson (1990) found that experts solving geometry problems made inferences that were strongly tied to geometry diagrams, and that features in the problem diagrams cued relevant problem-solving steps. Koedinger and Anderson found that the problem solving steps mentioned and skipped by experts could be successfully predicted by a model (the Diagram Configuration Model) that parsed diagrams into key geometric configurations and used these configurations to cue relevant schemas. Development of skilled performance in geometry, then, likely requires targeted attention to relevant diagram features as well as association of those features with relevant geometry rules.

Findings from these expert studies demonstrate the importance of *meaningful* connections between visual representations and domain knowledge, making it unlikely that learning would be supported by increasing shallow attention to visual representations alone. Research suggests that novices do, in fact, attend to visual representations during learning but that they often cannot connect visual features to meaningful information. Lowe (1993; 1999) has found that novices often are unable to discriminate between relevant and irrelevant aspects of science visualizations, and are easily distracted by domain-irrelevant but perceptually-salient features. In geometry, Lovett and Anderson (1994) found that diagrams, not problem logic, form the basis of novice memories for geometry proof. Moreover, geometry problems that used the same diagram but required different underlying solutions were solved significantly less often than when the problems with differing logic were accompanied by different diagrams. Thus, superficial or isolated use of diagrammatic information can compromise problem-solving performance.

Methods for Coordination of Visual Information

Leveraging the potential of visual information in problem solving requires that students form meaningful links between visual information and to-be-learned concepts that are typically expressed in text. Several techniques that coordinate visual and verbal information sources during learning have been studied as methods to reduce the extraneous cognitive load associated with search for relevant visual features and mapping between visual and verbal information in the learning materials. These techniques include spatial integration of textual information into geometry diagrams (Tarmizi & Sweller, 1988), and visual linking methods such as matched colors (Kalyuga, Chandler, & Sweller, 1999; Kozma, 2003) or simultaneous onset of information (Kozma, 2003).

Coordination methods focused on reducing extraneous cognitive load have generally promoted student learning, but an alternate explanation for observed benefits may be that visual-verbal coordination prompts students to focus on key features in visual representations and provides (passive) encouragement to integrate across existing representations.

In fact, requiring learners to actively integrate—using a drag-and-drop interface—text with relevant features of a visual diagram has been shown to result in better learning than a non-interactive, pre-integrated set of materials that should reduce extraneous cognitive load, especially when assessing deep learning from complex learning materials (Bodemer, Ploetzner, Feuerlein, & Spada, 2004). Thus, interaction and explicit identification of visual and verbal links may be useful methods to encourage connections between relevant visual and verbal information sources.

Objectives of the Study

In this study, we examined the effectiveness of two methods for connecting diagram elements to geometry knowledge: 1) the use of interactive visual diagrams during problem solving, and 2) the use of specific explanations stating which diagram features were relevant to the geometry rules that students used during problem solving. We were specifically interested in the effects on practiced problem solving, transfer tasks that tested deep understanding of geometry rules, and long-term retention of problem solving skills.

Method

Participants

Participants were 104 students in 10th grade Geometry at a rural Pennsylvania school. At posttest, we excluded students who had been absent for at least one of the study sessions or at posttest, leaving 81 students for analysis. An additional 23 students were absent at the delayed posttest, leaving 58 students for analyses. The timing of this study corresponded to the placement of the curriculum in the class schedule; the relatively high attrition at delayed posttest is likely due to a high absentee rate in the first school week following winter vacation when the delayed posttest was given. Total attrition was comparable across conditions, as seen in Table 1.

The Geometry Cognitive Tutor

Current research was implemented as an extension of the Cognitive Tutor, an intelligent tutoring system built upon the ACT-R theory of learning and cognition (Anderson & Lebière, 1998) that has been used successfully to support student learning in algebra (Anderson, Corbett, Koedinger, & Pelletier, 1995; Koedinger, Anderson, Hadley, & Mark, 1997) and geometry (Aleven & Koedinger, 2002). Cognitive Tutors support student learning by doing; the tutor selects problems for students to complete during practice, forming a model of students' competencies based on their success with skills contained in those problems. At every problem-solving step, the Cognitive Tutor provides feedback on student responses, gives hints upon request or after repeated errors, and continually tracks students' skill development. Other publications (e.g., Aleven & Koedinger, 2002; Anderson et al., 1995; Corbett, McLaughlin, & Scarpinatto, 2000) have described development details of the Cognitive Tutor. For the purposes of this research, we did not modify the ways in which the Geometry Cognitive Tutor modeled student knowledge, nor the content of the tutor curriculum (problems, hints, etc.). As seen in Table 1, we varied the site of student interaction with the tutor (a textual solution table vs. the visual problem diagram) and the type of explanation required for problem-solving steps (whether students were required to state geometry rules only vs. the geometry rule *and* its application to the diagram).

Table 1: Experimental conditions, with sample sizes at posttest and delayed posttest assessment.

		Site of Interaction	
		Table	Diagram
Type of Explanation	Geometry Rule Only	Posttest: n = 17 Delayed Posttest: n =12 *Attrition n = 14*	Posttest n = 20 Delayed Posttest: n =15 *Attrition n = 9*
	Geometry Rule & Diagram Application	Posttest n = 22 Delayed Posttest: n =15 *Attrition n = 11*	Posttest n = 22 Delayed Posttest: n =16 *Attrition n = 11*

Explanations in the Geometry Cognitive Tutor are implemented as menu-based selections. Previous research has shown that menu-based explanations are successful in supporting student learning (Aleven & Koedinger, 2002). In the current research, two types of menu-based explanations were implemented during student practice in the Geometry Cognitive Tutor. *Geometry rule* explanations required students to justify each problem-solving step by selecting the geometry rule that they had used to calculate their answer. *Diagram application* explanations required students to select the known diagram element(s) to which the selected geometry rule applied. Figure 2 shows a screen shot of the experimental interface with explanations relevant to the depicted problem.

The second factor—the site of interaction—varied the interface location where students interacted with the tutor. In the diagram interaction condition, students clicked on question marks in the diagram to open a nearby work area where all answers and explanations were entered. Once a numerical answer was accepted, it was displayed in the appropriate diagram location. The diagram interactive condition can be seen in Figure 1; the student has solved Arc EO, and is currently entering the answer and explanations for Angle OTE in the work area visible in the bottom left corner of the screen.

In the table interaction condition, the diagram is visible but not interactive and the diagram does not change during problem completion. Students can see question marks in the diagram that mark to-be-solved items, but they cannot click on these icons and accepted answers do not appear in the diagram. All answers and explanations are entered as text in the solution table seen in the upper right corner of Figure 1, and accepted answers are displayed in this table. In the diagram condition, the table is visible and automatically displays student answers but it is not interactive.

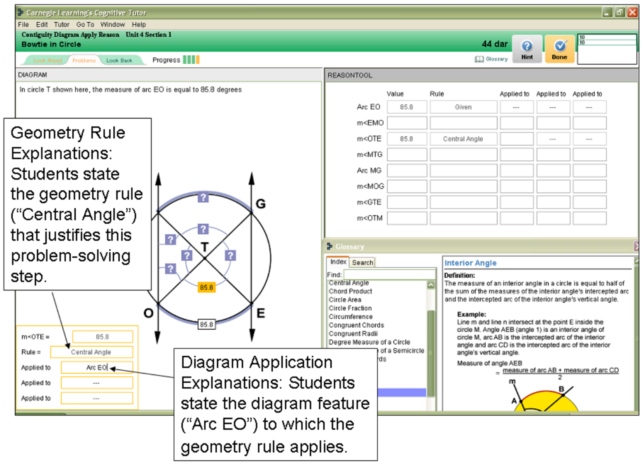

Figure 1: Student explanations of problem-solving steps, as implemented in the diagram interaction condition.

Assessments

Posttest The posttest assessment included 8 problem-solving situations with two questions per problem, for a total of 16 questions. Question responses included skills practiced in the cognitive tutor (answers and geometry rules) as well as transfer skills that had not been practiced by all students (solvability decisions and diagram application explanations).

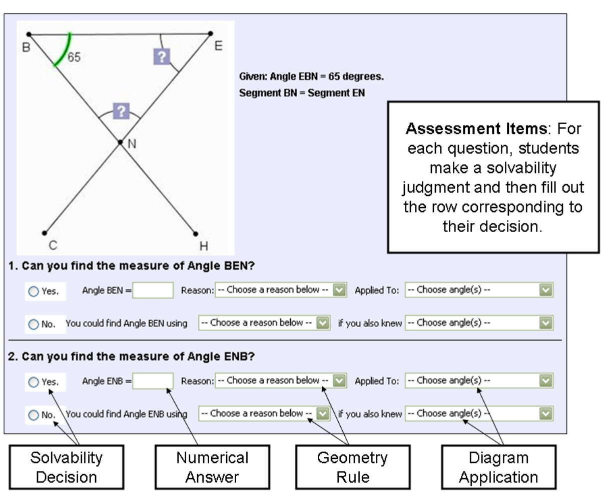

Figure 2: Example assessment problem.

As seen in Figure 2, each problem presented a diagram accompanied by given information, such as the measure of one or more angles and information about geometry relationships present in the diagram (e.g., parallel lines or equal line segments). Questions asked whether there was enough information to find a specific diagram element, “Can you find the measure of Angle BEN?” If students selected “Yes,” they then solved for the angle’s numerical measure, and indicated the geometry rule they used to find their answer as well as the known diagram element that allowed them to use their selected geometry rule. If students selected “No,” they then indicated a geometry rule that could be used to solve the problem and the additional diagram information that would be needed to do so.

Delayed Posttest The delayed posttest included four problem solving situations with two questions per problem, for a total of eight questions. Questions were isomorphic to problems on the posttest.

Tutor Log Data Every student transaction with the Geometry Cognitive Tutor is recorded in a log file that includes information about the problem and step being attempted, the type of student action (e.g., hint request, answer input), and a time stamp. These data allow indirect assessment of student processes during learning. In this research, we analyze the amount of time taken to enter answers and to state geometry reasons as a measure of potential cognitive load in the different conditions.

Procedure

Students participated in the study as part of their normal classroom curriculum, in which the Geometry Cognitive Tutor is used to augment teacher-led lessons and activities. Students practice geometry problem solving using the intelligent tutor for one classroom block (approximately 1 hour 15 minutes) each week. All students spent three classroom blocks working in the angles units of our experimental version of the Geometry Cognitive Tutor, taking a posttest in the fourth week. One month following the posttest, students completed a delayed posttest. Students were instructed to do their best to answer every question, and to take a guess if they were unsure of an answer.

The study was conducted as a 2 X 2 design. Grade-matched quartets of students were randomly assigned to the four experimental conditions within each of the participating classrooms. All classes were taught by the same teacher. The classroom teacher was instructed to interact with students as usual, providing typical levels of help and support during use of the tutor.

Results

Student performance at posttest and the tutor log data were analyzed using a multiple analysis of covariance (MANCOVA) on the 81 students with complete data at posttest; student progress in the Geometry Cognitive Tutor prior to the start of the study was used as the covariate. Prior tutor progress is a useful covariate because it reflects both student grades and prior knowledge. In the studied classrooms, students' tutor progress is used to calculate a significant portion of the class grade and, since progress in the Cognitive Tutor is self-paced, tutor progress gives a more accurate indication of exposure to geometry concepts than the concepts covered in class.

Student performance at delayed posttest was also analyzed by a MANCOVA with prior tutor progress as the covariate, but this analysis was conducted on the 58 students who had complete data at delayed posttest.

Posttest Performance

Practiced Skills At posttest, success with problem-solving skills practiced in the tutor (finding numerical answers and stating geometry rules) were not different for any experimental condition. Neither diagram interaction nor explaining the connection between geometry rules and diagrams during intelligent tutoring practice led to significantly better problem solving or rule-based explanations in the short term. Given extended student practice in an already-successful intelligent tutor that supports mastery learning, it is not particularly surprising that students perform similarly on these practiced items immediately after tutoring.

Transfer Tasks The posttest also included items that had not been practiced during intelligent tutoring. Solvability decisions were required for every question at posttest, but were not practiced during tutoring by any experimental condition. In the tutor, all problems can be solved and this may lead students to apply shallow strategies during practice. For example, students may calculate an answer using a common formula (e.g., subtract a given value from 90 or 180) and enter a recently-used rule without deeply understanding its application to the current problem. Solvability decisions, in contrast, require students to analyze both the problem diagram and the given information to determine if there is a geometry rule that can be appropriately applied to the problem situation.

As reflected in the means in Table 2, at posttest students who had interacted with diagrams tended to outperform students who had worked with tables in detecting solvable and unsolvable problems ($F_{(1, 76)} = 2.70$, $p = .10$). The type of explanation completed did not affect solvability decisions ($F < 1$).

A second type of transfer item is the diagram application items. These items require students to indicate the diagram features (typically one or two angles) that are used in the application of the geometry rule selected in their answer. Experimental conditions differed in whether or not they had practiced this skill in the tutor. Students in the *geometry rule and diagram application* explanation condition did practice this skill during tutoring; they selected a geometry rule and the relevant diagram features at every problem-solving step during practice and the tutor provided feedback for these explanations. However, students in the *geometry rule only* explanation condition received no practice or feedback in selecting diagram elements relevant to geometry rules. Thus, for students in the *geometry rule only* explanation condition, the rule-diagram analysis items were a transfer item that tested their deep understanding of geometry rules.

As seen in Figure 3, students in the diagram interaction conditions performed better on diagram application items than students in the table interaction condition ($F_{(1, 76)} = 6.23$, $p = .02$). This effect is driven by student performance in the *geometry rule only* explanation condition, where the diagram application items are a measure of transfer. Separate analysis of the *geometry rule only* explanation conditions shows that diagram interaction is powerful in supporting effective connections between visual representations and domain knowledge. When diagram application explanations are not required during practice, diagram interaction leads to significantly greater success linking diagrams to rules ($F_{(1, 34)} = 11.51$, $p = .002$).

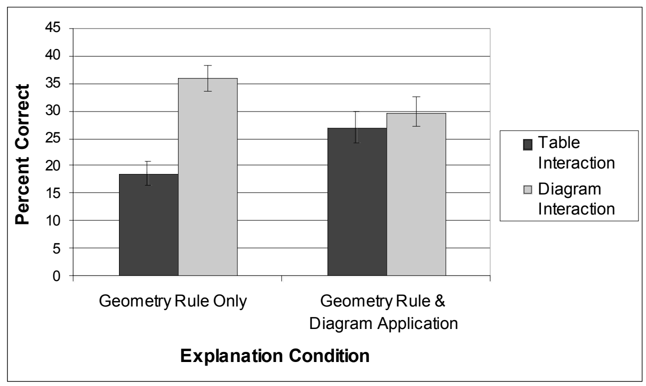

Figure 3: Mean (+ SE) performance on diagram application items at posttest.

Interaction with diagrams provides implicit but powerful support for making meaningful connections between visual and verbal information sources. Although the addition of diagram application explanations during practice also improved knowledge of diagram-rule links, there were no additive benefits associated with the additional explanation activity.

Delayed Posttest Performance

Practiced Skills At delayed posttest, students who worked with the interactive diagrams showed a significant advantage in the accuracy of their problem-solving answers compared to students who worked with the interactive tables ($F_{(1, 53)} = 4.03$, $p = .05$). In contrast, the type of explanation produced during practice had no effect on long-term retention of problem-solving skills. As seen in Figure 4, diagram interaction supported successful problem solving as measured by correct numerical answers for geometry problems. Overall, the problem-solving success for students who interacted with the textual solution table during problem solving declined by an average of 34% in the month following practice, compared to an 11% decline for students who interacted with the visual diagrams during practice.

Table 2: Posttest, delayed posttest, and log data means and (*standard deviations*).

	Table Interaction		**Diagram** Interaction	
	Explain **Geometry Rule**	Explain **Geometry Rule & Diagram Application**	Explain **Geometry Rule**	Explain **Geometry Rule & Diagram Application**
Posttest Solvability Decisions	59.2 (*20.1*)	56.0 (*25.0*)	65.6 (*21.3*)	65.1 (*22.4*)
Posttest Numerical Answers	35.8 (*26.0*)	31.8 (*34.7*)	43.8 (*33.9*)	37.9 (*28.6*)
Posttest Geometry Rules	20.2 (*16.6*)	22.4 (*24.2*)	25.6 (*21.3*)	22.7 (*25.8*)
Posttest Diagram Application	18.8 (*18.1*)	27.0 (*25.4*)	35.9 (*20.9*)	29.8 (*25.6*)
Delayed Posttest Solvability Decisions	56.3 (*18.8*)	47.5 (*15.8*)	57.5 (*22.6*)	63.3 (*16.8*)
Delayed Posttest Numerical Answers	20.0 (*27.0*)	24.0 (*28.5*)	36.0 (*32.3*)	36.3 (*29.4*)
Delayed Posttest Geometry Rules	14.6 (*18.3*)	12.5 (*15.7*)	15.8 (*22.9*)	25.8 (*28.3*)
Delayed Posttest Diagram Application	14.6 (*17.5*)	21.7 (*17.3*)	23.3 (*21.6*)	23.4 (*25.0*)
# Problems Completed	54.9 (*30.1*)	53.4 (*28.8*)	48.1 (*25.2*)	53.7 (*25.9*)
Average Time (sec): Answers	28.8 (*16.0*)	27.4 (*15.5*)	26.2(*13.0*)	24.0 (*12.0*)
Average Time (sec): Geometry Rules	9.3 (*3.5*)	10.3 (*7.8*)	9.4 (*2.9*)	10.7 (*6.6*)

The pattern of means for geometry rule answers also favors students who interacted with diagrams during problem solving (see Table 2), but this effect is not statistically significant ($F_{(1, 53)} = 1.79$, $p = .19$)

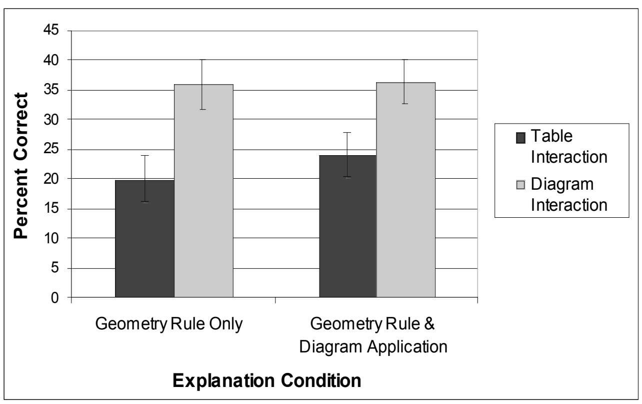

Figure 4: Mean (+ SE) performance on numerical answers at delayed posttest.

Transfer Items At delayed posttest, students who worked with the diagram interactive tutor tended to make more accurate solvability decisions than students who interacted with the textual tables during practice ($F_{(1, 53)} = 3.11$, $p = .08$). Explanations did not influence solvability decisions at delayed posttest ($F < 1$). For diagram application items, no significant condition differences were found.

Process Analyses Using Tutor Log Data

The current results show that diagram interaction can support deep learning and long-term knowledge retention. However, the learning outcomes themselves do not address whether the benefits of diagram interaction stem primarily from support in making meaningful connections between visual and verbal information during learning, or a reduction in extraneous cognitive load involved in visual search for relevant diagram features and in mapping between the visual diagram elements and textual information in the table.

Log data recorded during student practice in the tutor offers indirect evidence that extraneous cognitive load may not be a major factor in these results. If extraneous load involved in visual search and mapping were a major impediment to student learning, we would expect students who interacted with the table during learning to input their initial answers and reasons more slowly during practice. For the first attempt at any problem-solving step, angles names referenced in the table must be located in the diagram and angle measures displayed in the table must be mapped to the diagram. This visual search and mapping time should add to problem-solving time. In contrast, interactive diagrams reduce or eliminate extraneous cognitive load by making it unnecessary to search for angles referenced in the table or to map between the table and the diagram. Thus, answers and reason attempts in the diagram interaction condition should reflect problem-solving time without extraneous processes.

Analyses of student transactions recorded in tutor log data showed no evidence that extraneous cognitive load slowed student actions in the tutor. Students who interacted with the tables and diagrams during intelligent tutoring practice did not differ significantly in the time that they took to enter their first attempt at an answer ($F_{(1, 76)} = 1.04$, $p = .31$) or a reason ($F < 1$) for problem-solving steps. Students also did not differ in the number of problems that they were able to complete during intelligent tutoring ($F < 1$), arguing against the possibility that extraneous cognitive load manifested not in the time to complete initial attempts, but in greater difficulty completing problems after incorrect responses.

A lack of time differences does not mean that extraneous cognitive load cannot be influencing student work in the tutor, nor that students working with the tables are engaging in identical cognitive processes to students working with the diagrams. Students interacting with the diagrams may be more likely to engage in productive processes—such as self-explanation or noticing related visual elements—that produce an equivalent time course of action. However, log data results do argue against the likelihood that a reduction in extraneous cognitive load can be considered the central explanation for the benefits of visual interaction seen here.

Conclusions

Results showed diagram interaction to have surprisingly robust benefits for learning. Interactions with geometry diagrams during intelligent tutoring supported the long-term retention of practiced problem-solving skills, and promoted student success with transfer tasks that required meaningful connections between diagrams and geometry rules. The addition of explanations that explicitly connected diagram elements to geometry rules did not demonstrate strong effects on learning, showing generally weaker benefits than simple diagram interaction.

Why didn't the addition of explanations that focused on diagram elements have more impact? One possibility may be that diagram application explanations typically were the last action performed on each problem-solving step and may have been largely redundant with processing that occurred earlier (in determining the numerical answer and geometry rule for the same step). In fact, on average, students' diagram application explanations were correct 88% of the time. More meaningful connection of visual representations may occur as students struggle to find appropriate solutions to problems, making it necessary to embed visual interaction at these earlier, critical times. It is also possible that the diagram application explanations did not prompt students to attend to relevant diagram features in the way we anticipated. Students may have focused not on diagram configurations, but on the numerical values in the diagram (or table) that they used to calculate their answer for the same step. In current work, we are exploring the addition of diagram interaction at key opportunities for learning, by supporting student highlighting of relevant diagram features following student errors. In other work, we also are exploring problem-solving processes associated with student development of visual-verbal connections via think-aloud protocols collected from students interacting with tables or diagrams during tutoring. Future work should continue to explore the rationale for visual interaction benefits, with particular focus on specifying the processes involved in visual-verbal coordination during learning.

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