Title
Learning during Intelligent Tutoring: When Do Integrated Visual-Verbal Representations Improve Student Outcomes?

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 32(32)

ISSN
1069-7977

Authors
Butcher, Kirsten
Aleven, Vincent

Publication Date
2010

Peer reviewed

Learning during Intelligent Tutoring: When Do Integrated Visual-Verbal Representations Improve Student Outcomes?

Kirsten R. Butcher (kirsten.butcher@utah.edu)
Department of Educational Psychology, University of Utah, 1705 E. Campus Center Drive, MBH 327
Salt Lake City, UT, 84108 USA

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

Abstract

Research has shown that integration of visual and verbal information sources during learning promotes successful student outcomes. However, it is unclear whether it is better to provide students with integrated visual-verbal representations, or to require them to build such integrated representations themselves. In a classroom study, three conditions were used to explore the impact of integrated visual-verbal representations that emphasized rule-diagram mappings in geometry. Students viewed highlighted rule-diagram mappings during learning, generated these mappings themselves, or saw only numerical information embedded in diagrams (control). Students' problem-solving knowledge was measured at posttest and delayed posttest. Overall, students who generated rule-diagram mappings during intelligent tutoring demonstrated better long-term understanding of geometry principles, but effects were only visible at delayed posttest. Results show that integrated visual-verbal representations best support deep learning when they help the learner make connections between features of a visual representation and relevant domain information, and student interactions can be an effective method to scaffold these connections.

Keywords: Intelligent tutoring; Diagrams; Problem solving; Long-term retention; Visual representations

Introduction

Research in multimedia learning has demonstrated that adding visual representations to text materials frequently improves students' learning outcomes (e.g., Carney & Levin, 2002). Studies of cognitive processing with multimedia materials have demonstrated that visual materials support learning by increasing students' generation of effective self-explanations during study (Ainsworth & Loizou, 2003; Butcher, 2006).

However, not all visual representations are equally effective in supporting learning. Diagrams have been shown to be more effective when verbal materials (such as textual labels for diagrams) are integrated directly into the visual representation (e.g., Hegarty & Just, 1993) before they are presented to students. Other research has shown that student-driven integration of visual and verbal materials supports learning with complex materials and may promote goal-oriented behaviors during subsequent, self-directed learning (Bodemer, Ploetzner, Bruchmüller, & Hacker, 2005). Together, these research results suggest clear benefits of integrated visual-verbal representations for learners. However, they also raise the question of whether learners should be provided with integrated visual representations or if it is better to require learners to generate the integrated representations themselves.

The question of whether or not to provide students with integrated visual-verbal representations highlights the *assistance dilemma* (Koedinger & Aleven, 2007). The assistance dilemma refers to the difficulty of deciding when interactive learning environments should provide vs. withhold information in order to support optimal student learning. The assistance dilemma reflects a technology-based application of the long-standing instructional concept of *desirable difficulty* (e.g., Bjork, 1994). Desirable difficulty refers to the finding that increasing the difficulty of a learning activity can improve long-term knowledge outcomes, even though performance during training may suffer. Desirable difficulty argues against a common assumption that optimal learning is facilitated when instructional materials are designed to ease student comprehension and increase successful performance. Thus, a key question for intelligent tutoring systems using visual representations is: when should intelligent tutoring systems provide integrated visual-verbal support vs. withhold this support in order to optimize student learning outcomes?

Connecting Diagrams to Domain Knowledge

The assistance dilemma and the concept of desirable difficulty raise the important question of when to provide vs. withhold integrated visual-verbal representations for optimal learning. However, a central question is what type of integrated representation is most beneficial to learners.

Much of the research on integrated visual representations has made use of visuals that physically embed additional information into a visual representation. Multimedia presentations have been shown to support deeper understanding of instructional materials when they provide students with diagrams into which textual labels and definitions have been embedded (e.g., Hegarty & Just, 1993). In geometry, research has shown that students learn more when they are provided with representations in which numerical measures have been integrated into diagrams (Tarmizi & Sweller, 1988) or when they are provided with color-coded highlighting that links text references (e.g., a reference to angle ABC) with relevant diagram elements (Kalyuga, Chandler, & Sweller, 1999). Overall, research shows clear benefits for integrated visual-verbal representations during learning. However, integrated visual-verbal representations may not, in and of themselves, prompt learners to make connections to key domain ideas.

Evidence suggests that individuals with deep domain understanding tend to exhibit strong connections between domain concepts and visual representations. For example, experts in geometry use key diagram configurations to cue relevant geometry knowledge (i.e., theorems and principles) during problem solving (Koedinger & Anderson, 1990). During mathematical problem-solving, mathematicians repeatedly analyze connections between generated visual representations, changing goals, and the emerging problem situation (Stylianou, 2002).

Unlike experts, novices do not demonstrate close connections between visual representations and domain knowledge during problem solving. In geometry, novices tend to process diagrams in isolated ways, focusing on visual features without considering their relationship to deeper, conceptual aspects of problems (Lovett & Anderson, 1994). Ainsworth (2006) argues that a central cognitive task in learning with multiple representations is developing an understanding of the relationship between a visual representation and relevant domain information.

One way to support novice learning in geometry, then, may be to scaffold student interactions with visual representations in a way that improves their understanding of the relationship between visual features of geometry problems (i.e., geometry diagrams) and the geometry principles/rules used in problem solving. In geometry, problem solving requires that learners connect meaningful diagram configurations to relevant geometry principles. For example, in Figures 2 and 3, angle ABC is an *interior angle, same side* to angle BCD. Learners should recognize that the diagram contains two parallel lines (AB, DC) intersected by a transversal (BC). Angles ABC and BCD are on the interior of the parallel lines, and on the same side of the transversal. Thus, they are *interior angles, same side* and can be solved using this rule. In this study, we used highlighted diagram features to demonstrate the mapping between diagrams and relevant geometry principles in the domain (see Figures 2 and 3); hereafter, these are referred to as diagram-domain representations.

Integrated Diagrams in Intelligent Tutoring

In previous research (Butcher & Aleven, 2007, 2008), we explored the use of interactive visual diagrams as a method to support the development of integrated visual-verbal knowledge during intelligent tutoring in geometry. The research vehicle for this work was the Geometry Cognitive Tutor, an intelligent tutoring system (ITS) grounded in cognitive theory that provides multiple forms of support for student learning by doing: tracking students' knowledge development using a model of student competency, selecting problems for students to complete that match identified learning needs, structuring problem-solving steps for students, giving feedback on all student actions, and providing hints upon student request or when the student makes repeated errors. Details about Cognitive Tutor features are available elsewhere (e.g., Anderson, Corbett, Koedinger, & Pelletier, 1995).

Butcher and Aleven (2007, 2008) varied the site of student interaction during geometry problem solving in an intelligent tutoring system: students used either an *interactive diagram* or a *solutions table* version of the intelligent tutoring system (see Figure 1). Students using the interactive diagram tutor clicked directly on diagram elements to enter answers and receive feedback, thus creating an integrated representation in which numerical answers were embedded in the visual representation. Students in the control condition used the solutions table to enter their answers and receive feedback. Although the solutions table kept a running record of students' answers, numerical values were not integrated directly into the diagram. Results showed that students who interacted with the diagrams to develop an integrated representation learned geometry principles more deeply (as evidenced by transfer task performance: Butcher & Aleven, 2007) and retained their problem-solving skills for longer periods of time (Butcher & Aleven, 2008).

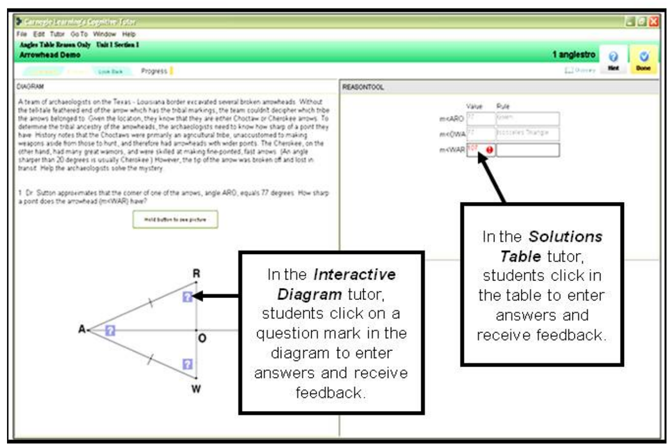

Figure 1: Condition-based differences in interactions with an intelligent tutor (Butcher & Aleven, 2007, 2008).

Despite the success of these diagram interactions in an already-successful intelligent tutoring system, there was still ample room for student improvement at assessment. It is possible that diagram interaction helped students focus on relevant visual elements during problem solving, but the integrated representations that students developed did not make it clear how diagram elements mapped onto domain information.

Student Generation of Integrated Representations
Simply providing students with visual representations that connect diagrams features to domain information may not be optimal for learning. Research has shown that requiring

students to actively integrate visual and verbal information (i.e., using a drag-and-drop interface to produce a labeled diagram) improves learning outcomes and increases the quality of students' self-directed learning behaviors (Bodemer et al., 2005). However, it is unclear whether interactions that emphasize diagram-domain mappings during problem-solving practice can improve learning more than interactions that build integrated visual-verbal representations (cf., Butcher & Aleven, 2007, 2008).

The purpose of this study was to explore the potential benefits of providing students with integrated representations that emphasized the mapping between diagram elements and domain information during intelligent tutoring vs. requiring students to generate these integrated representations. Both conditions were compared to a control condition in which students interacted with diagrams to embed numerical information into the diagrams (i.e., student interactions created an integrated, visual-verbal representation that did not emphasize domain connections).

Method

Participants

Eighty-three students from five 10th grade geometry classrooms at a vocational school in rural Pennsylvania participated in the study as part of their normal classroom curriculum, which included practice with the Geometry Cognitive Tutor once a week (one 75 min session per week).

Grade-matched triplets of students were identified within each class, using students' first semester geometry grades as a measure of prior knowledge. From every grade-matched triplet, one student was randomly assigned to each of the three experimental conditions described below.

Materials

Student-Highlighting Condition The purpose of the student highlighting condition was to require student interactions with the intelligent tutor that generated integrated diagram-domain representations during problem-solving practice in the Cognitive Tutor. In this condition, if a student entered an incorrect answer or reason during practice, s/he was locked out of the numerical answer field until s/he identified the correct geometry principle needed to solve the problem-solving step. Once the correct principle was identified, students highlighted the diagram features relevant to that principle (see Figure 2). These highlights created an integrated diagram-domain representation of the problem situation. As seen in Figure 2, highlighting was scaffolded by a list of diagram features that appeared after students entered a correct geometry principle for a problem-solving step. Students were required to highlight each diagrammatic feature in the list (e.g., for *Interior Angles, Same Side*, students were prompted to highlight the parallel lines, the transversal, and the two relevant angles).

Students highlighted a diagrammatic feature by clicking directly on it; students could deselect a highlighted feature by clicking on it again. Students received immediate feedback on each highlighted feature in the diagram. Incorrect highlights turned red on the diagram and in the accompanying answer area. Correct highlights were kept on the screen until the problem-solving step was completed.

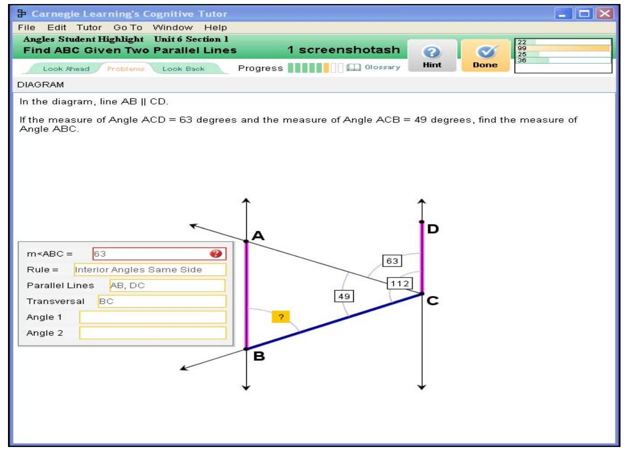

Figure 2: In-progress student highlighting of diagram for *interior angles, same side* rule. Parallel lines and transversal have been highlighted so far.

Tutor-Highlighting Condition This condition utilized the same representations as the student-highlighting condition, but in this case the tutor *provided* students with the highlighted diagram-domain representation. Following a problem-solving error and student identification of a relevant geometry principle, the tutor automatically highlighted the diagram. The screen shot in Figure 3 shows the result of the tutor highlighting; it is important to note that the final representations in the student- and tutor-highlighting conditions were equivalent, differing only in whether the student or tutor generated the representation.

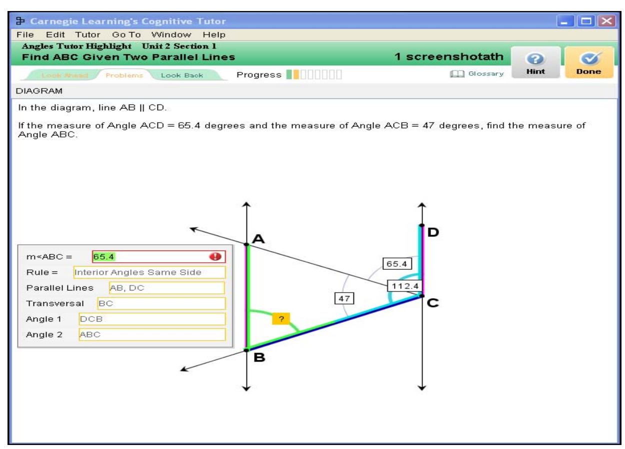

Figure 3: Tutor-highlighted diagram following student error

No Highlighting (Control) The control condition was the successful interactive-diagram version of the Geometry Cognitive Tutor from Butcher and Aleven (2007). This condition did not involve any highlighting of visual diagram features by either students or the intelligent tutoring system.

However, students entered answers directly into the geometry diagram; this created an integrated visual-verbal representation in which numerical values were embedded in the visual diagram.

Assessments *Problem-Solving Pre- and Posttest* The problem-solving pre- and posttest consisted of 16 total items. For each to-be-solved item, students needed to provide a numerical answer (e.g., 65º) and the geometry principle that was used to derive the numerical answer (e.g., Vertical Angles). The problem-solving posttest was the same as the pretest, but problems appeared in a different order. One point was given for each correctly-solved angle and correctly-identified principle. Due to a technical error and student absences, data was collected from 68 participants at pretest and from 70 students at posttest.

Delayed Posttest The delayed posttest was given on the computer, four weeks following the posttest. The delayed posttest followed the same format as the pre- and posttest, but with less complex problems. Students received one point per correctly-solved angle and correctly-identified geometry principle, for a maximum of 8 points on each dependent measure. Due to high numbers of student absences in the week that the delayed posttest was given (near the end of the school year), 41 students completed the delayed posttest.

Procedure

Participants were given up to 30 minutes to complete the pretest during their geometry class. Pretests were delivered via computer; students were instructed to try their best to complete the problems, and to take a guess if they were not sure of an answer. After completing the pretest, students worked with their assigned tutor version for four weeks during a 75-minute, weekly computer lab. This computer lab was a normal part of the students' geometry classes, and all students had used non-experimental versions of the Geometry Cognitive Tutor during previous sessions in the computer lab. The Geometry Cognitive Tutor used in each condition did not differ in problem content, the number of required problems, or the knowledge models used by the Cognitive Tutor.

One week after completing the study, students were given up to 45 minutes to complete the posttest during their geometry computer lab. A delayed posttest was administered one month following the posttest. Participants had up to 30 minutes to complete the delayed posttest.

Results and Discussion

Training Performance

In the Geometry Cognitive Tutor, learners provide a numerical answer and a geometry principle (aka "rule) that justifies the numerical answer for each problem-solving step. Log data from student practice with the Geometry Cognitive Tutor were analyzed to assess performance on the first answer and geometry rule attempted by a learner for each problem step during practice. Data were calculated only for problem steps that were not given in the problem statement. That is, data were analyzed only for problem steps in which students needed to apply a geometry principle in order to calculate a correct answer. Student progress in the Geometry Cognitive Tutor was self-paced and, in general, was slower than anticipated by either the experimenters or the students' classroom teachers. Because the intelligent tutoring system requires mastery learning before students can continue to the next instructional unit, not all students completed the three instructional units in the experimental version of Geometry Cognitive Tutor. In total, 72 students produced tutor log data in unit 1 (control: n = 23, tutor-highlighting: n = 25, student-highlighting: n = 24). Forty-five students reached unit 2 (control: n = 14, tutor-highlighting: n = 16, student-highlighting: n = 15), but only 27 students reached unit 3 (control: n = 10, tutor-highlighting: n = 8, student-highlighting: n = 9).

Due to the drop in student numbers at each instructional unit, three multivariate analyses of covariance (MANCOVAs) were used to assess student performance in each unit of the tutor. Dependent variables were the percent correct of students' initial attempts at numerical answers and geometry rules for each not-given problem-solving step. Students' pretest scores on numerical answers and geometry rules were used as covariates to control for prior knowledge. As seen in Figure 4, unit 1 data demonstrated no significant differences in practice performance on numerical answers or geometry rules (Fs < 1).

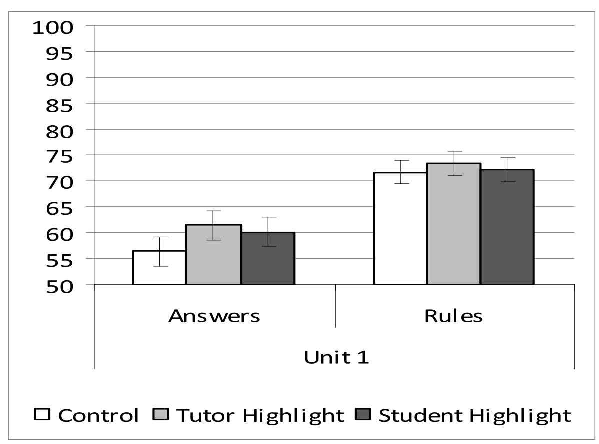

Figure 4: *M* (and *SE*) percent correct for answers and geometry rules in unit 1 during intelligent tutor practice

Unit 2 also failed to show any significant condition differences in problem-solving performance on answers or geometry rules (Fs < 1). For the few students who reached unit 3, students who interacted with the tutor to generate integrated diagram-domain representations had a slight, though non-significant, advantage on numerical answers ($F_{(2, 22)} = 2.7$, $p < .09$). However, as seen in Figure 5, there were no differences in students' accuracy in using geometry rules to justify their problem-solving steps during practice.

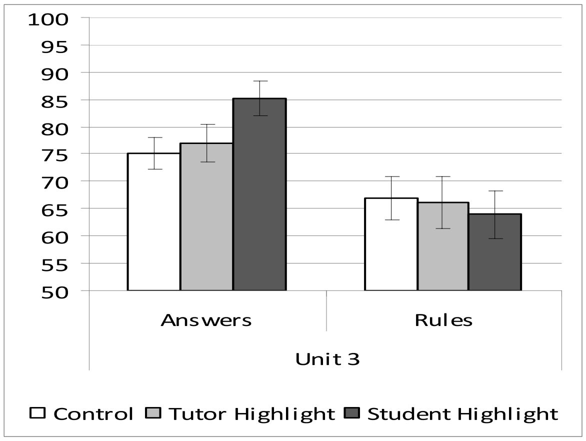

Figure 5: *M* (and *SE*) percent correct for answers and geometry rules in unit 3 during intelligent tutor practice

Problem-Solving Performance

Overall, 33 students completed all three assessments (control: n = 13, tutor-highlighting: n = 11, student-highlighting: n = 10). Data were analyzed using a repeated-measures MANOVA, where test time (pretest, posttest, delayed posttest) was the repeated factor.

For numerical answers, results showed no test time by condition interactions (Linear: $F < 1$; Quadratic: $F_{(2,\ 31)} = 1.48$, $p > .24$). However, as seen in Table 1, students' performance on geometry principles showed a significant test time by condition interaction (Linear: $F_{(2,\ 31)} = 4.97$, $p = .01$, $\eta_p^2 = .24$; Quadratic: $F_{(2,\ 31)} = 3.28$, $p = .05$, $\eta_p^2 = .18$). Students in the student-highlighting condition were best able to justify their problem-solving steps with geometry rules at delayed posttest; however, no differences were seen at the short-term posttest. Figures 6 and 7 show the pattern of means on the posttest and delayed posttest, respectively, adjusted for pretest performance.

Table 1: *M* (and *SD*) percent correct on geometry rules

	Pretest	Posttest	Delayed Posttest
Control	18.2 (16. 7)	25.5 (14.3)	19.4 (18.0)
Tutor-Highlighting	11.1 (10.6)	23.2 (21.2)	17.7 (11.4)
Student-Highlighting	12.4 (7.2)	16.3 (13.6)	31.7 (14.2)

As seen in Figure 6, there were no significant condition differences at posttest. If anything, the pattern of results at posttest was consistent with a disadvantage for students who highlighted diagrams during practice. Although this may seem inconsistent with the overall pattern of performance in unit 3 during intelligent tutoring practice (see Figure 5), one should remember that not all students taking the posttest reached unit 3 in the intelligent tutor.

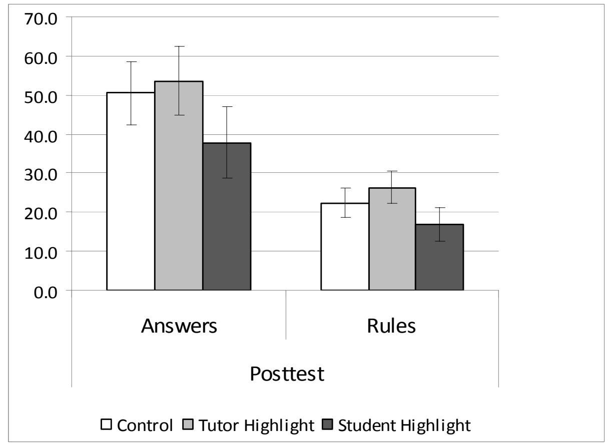

Figure 6: *M* (and *SE*), adjusted for pretest performance, on posttest numerical answers and geometry rules.

One month later, at delayed posttest, the data paint a different picture Although there were no differences in students' accuracy in providing numerical answers at delayed posttest, students who generated integrated diagram-domain representations during practice were better able to justify their problem-solving steps with relevant geometry rules. It is important to note that this advantage was found even though control students made use of integrated diagrams with embedded numerical answers. Moreover, the advantage cannot be attributed to additional information in the diagram-domain representations, as students who were provided with these representations by the tutor did not outperform the control group in correctly using geometry rules (see Figure 7).

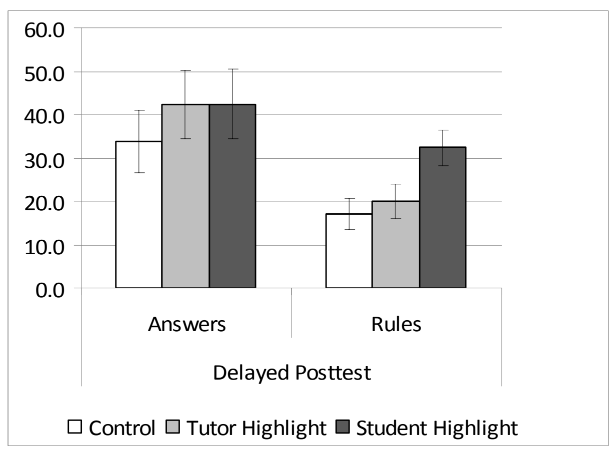

Figure 7: *M* (and *SE*), adjusted for pretest performance, on delayed posttest numerical answers and geometry rules.

To confirm results obtained from the small group of students with full assessment data, two additional analyses were conducted. First, a MANCOVA was used to assess performance changes for all 68 students with pre- and posttest data (control: n = 23, tutor-highlighting: n = 24, student-highlighting: n = 21). Dependent variables were performance on numerical answers and geometry rules at posttest; covariates were students' performance on answers and rules at pretest. Results were consistent with the small sample, showing no condition differences for either numerical answers or geometry rules (*F*s < 1). A second, similar MANCOVA was conducted for all 41 students with pre- and delayed posttest data (control: n = 14, tutor-highlighting: n = 13, student-highlighting: n = 14). Results again were consistent with the small sample, showing a significant advantage of the student-highlighting condition for geometry rules ($F_{(2, 36)} = 4.04$, $p = .03$, $\eta_p^2 = .18$), but not numerical answers ($F_{(2, 36)} = 1.38$, $p > .26$).

General Discussion

Overall, results show that *providing* integrated visual-verbal materials to students during intelligent tutoring does not improve students' learning outcomes. However, findings show that using *interactions to build* integrated diagram-domain representations can support long-term understanding. Students who generated integrated representations that emphasized diagram-domain mappings during problem-solving practice showed no performance advantages in using geometry principles at practice or posttest, but were best able to apply these principles one month following instruction.

Results are consistent with the idea that student interactions can support deep learning with visual information. However, results also argue that integrated visual-verbal representations best support deep learning when they help the learner make connections between features of the visual representation and relevant domain information. The current study shows that student interactions can be an effective method to scaffold these connections. Findings also demonstrate the importance of measuring long-term knowledge gains, as student performance during practice and short-term assessments may not provide an accurate picture of deep understanding.

Acknowledgments

The authors thank Octav Popescu, Carl Angiolillo, Michael Nugent, Grace Leonard, and Thomas Bolster for their contributions. Special thanks to Mark Schoming and Colleen Conko for assistance in the classroom. This work was supported in part by the Pittsburgh Science of Learning Center through funding from the National Science Foundation (SBE# 0354420, 0836012). The opinions and conclusions presented here are those of the authors and do not necessarily reflect the funding agency.

References

Ainsworth, S. (2006). DeFT: A conceptual framework for considering learning with multiple representations. Learning & Instruction, 16(3), 183-198.

Ainsworth, S., & Loizou, A. T. (2003). The effects of self-explaining when learning with text or diagrams. Cognitive Science, 27, 669-681.

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. Journal of the Learning Sciences, 4(2), 167-207.

Bjork, R. A. (1994). Memory and metamemory considerations in the training of human beings. In J. Metcalfe & A. Shimamura (Eds.), Metacognition: Knowing about knowing (pp. 185-205). Cambridge, MA: MIT Press.

Bodemer, D., Ploetzner, R., Bruchmüller, K., & Hacker, S. (2005). Supporting learning with interactive multimedia through active integration of representations. Instructional Science, 33, 73-75.

Butcher, K. R. (2006). Learning From Text With Diagrams: Promoting Mental Model Development and Inference Generation. Journal of Educational Psychology, 98(1), 182-197.

Butcher, K. R., & Aleven, V. (2007). Integrating visual and verbal knowledge during classroom learning with computer tutors. In D. S. McNamara & J. G. Trafton (Eds.), Proceedings of the 29th Annual Cognitive Science Society (pp. 137-142). Austin, TX: Cognitive Science Society.

Butcher, K. R., & Aleven, V. (2008). Diagram interaction during intelligent tutoring in geometry: Support for knowledge retention and deep understanding. In B. C. Love, K. McRae & V. M. Sloutsky (Eds.), Proceedings of the 30th Annual Conference of the Cognitive Science Society (pp. 1736-1741). Austin, TX: Cognitive Science Society.

Carney, R. N., & Levin, J. R. (2002). Pictorial illustrations still improve students' learning from text. Educational Psychology Review, 14(1), 5-26.

Hegarty, M., & Just, M. A. (1993). Constructing mental models of machines from text and diagrams. Journal of Memory and Language, 32, 717-742.

Kalyuga, S., Chandler, P., & Sweller, J. (1999). Managing split-attention and redundancy in multimedia instruction. Applied Cognitive Psychology, 13(4), 351-371

Koedinger, K. R., & Aleven, V. (2007). Exploring the assistance dilemma in experiments with cognitive tutors. Educational Psychology Review, 19(3), 239-264.

Koedinger, K. R., & Anderson, J. R. (1990). Abstract planning and perceptual chunks: Elements of expertise in geometry. Cognitive Science, 14(4), 511-550.

Lovett, M. C., & Anderson, J. R. (1994). Effects of solving related proofs on memory and transfer in geometry problem solving. Journal of Experimental Psychology: Learning, Memory, and Cognition, 20(2), 366-378.

Stylianou, D. A. (2002). On the interaction of visualization and analysis: the negotiation of a visual representation in expert problem solving. Journal of Mathematical Behavior, 21, 303-317.

Tarmizi, R. A., & Sweller, J. (1988). Guidance during mathematical problem solving. Journal of Educational Psychology, 80(4), 424-436.