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Improving Classroom Learning by Collaboratively Observing Human Tutoring Videos While Problem Solving

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Collaboratively observing tutoring is a promising method for observational learning (also referred to as vicarious learning). This method was tested in the Pittsburgh Science of Learning Center's Physics LearnLab, where students were introduced to physics topics by observing videos while problem solving in Andes, a physics tutoring system. Students were randomly assigned to three groups: (a) pairs collaboratively observing videos of an expert human tutoring session, (b) pairs observing videos of expert problem solving, or (c) individuals observing expert problem solving. Immediate learning measures did not display group differences; however, long-term retention and transfer measures showed consistent differences favoring collaboratively observing tutoring.

Keywords: collaboration, observational learning, vicarious learning, physics, problem solving

Observing tutoring has recently emerged as a promising new focus in the observational learning literature (Chi, Roy, & Hausmann, 2008; Craig, Driscoll, & Gholson, 2004). By *observing tutoring*, we refer to the process in which a learner sees and hears the dialogue between a tutor and a tutee without being able to participate in it. In observational learning (also labeled *vicarious* or *social learning*), information is gained by watching the learning process of another (Bandura, 1986; Gholson & Craig, 2006). Thus, observing tutoring can be considered a subcategory of observational learning.

In the present study and previous research by Chi et al. (2008), pairs of students solved problems collaboratively as they observed tutoring. This combination of collaborative problem solving and observing tutoring is called *collaboratively observing tutoring*. If collaboratively observing tutoring proves to be an effective method of learning, then it could provide a cost-effective alternative to human tutoring and intelligent tutoring systems (Alessi & Trollip, 1991; Anderson, Corbett, Koedinger, & Pelletier, 1995; Azevedo, & Bernard, 1995; Derry & Potts, 1998; VanLehn et al., 2005).

However, it is important to understand whether the benefits are due to the domain content of the videos (essentially, a worked example) or the tutorial content, which has affective overtones and is conversationally based. The current study compares collaboratively observing videos of one-on-one, expert human tutoring with observing videos of an expert demonstrating how to solve the same problems. That is, the videos show either a tutoring session or worked examples.

Observational Learning

Learning by observing has been investigated in several areas of research. For instance, in social psychology, studies have shown that people who watch someone acting aggressively tend to start acting more aggressively themselves (Bandura, 1969, 1986). Neuroscientists and developmental psychologists study imitative learning in humans and other species (e.g., Meltzoff, 2005). Learning by observing occurs in work settings (Latham & Saari, 1979) and is the first stage of Collins, Brown, and Newman's (1989) model–scaffold–fade account of cognitive apprenticeship. In much of this work, students learned by observing live humans, observing videos of humans, studying cartoons, and/or listening to audiotapes (Bandura, 1986; Gholson & Craig, 2006; Rogoff, Paradise, Mejía Arauz, Correa-Chávez, & Angelillo, 2003; Rosenthal & Zimmerman, 1978).

However, when the competence to be acquired is problem solving and the observed material is a problem plus all the steps required for its solution, then the material is called a *worked example*. Typically, the problem and its steps are presented on paper, in a video, or via click-through text. Considerable research has investigated how students learn from worked examples (Atkinson, Derry, Renkl, & Wortham, 2000). Although it might be interesting to compare modalities (video vs. paper, etc.), there is no doubt that students can learn from observation in all of them. Our

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concern is with the content presented to students, so we used video as the only presentation modality.

Whereas a common way of modeling a new skill is for the instructor to demonstrate it, another method is for the instructor to tutor a student with other students watching. For instance, a master tailor may show a senior apprentice how to sew an intricate joint while the other apprentices watch (Lave & Wenger, 1991), or a student may solve a math problem on the blackboard at the front of the class with the teacher's help. The demonstration is a monologue, whereas the tutoring session is a dialogue between the tutor and tutee.

Both types of presentation of material seem to have benefits. On the one hand, the demonstration (worked example) is probably coherent and certainly correct, whereas the tutorial dialogue may be incoherent and/or incorrect at times. From a purely cognitive point of view, the information as presented in the demonstration should be easier to learn than the information as presented in the tutoring session. On the other hand, the tutoring session might be more interesting. For instance, text has been found to have higher ratings of situational interest if it contains humans with whom the reader can identify (Hidi & Harackiewicz, 2000). The tutoring session may display self-regulatory behavior that the observers would be wise to emulate. The observers may adopt more realistic expectations for their own performance when they see another student struggle. Further, the dialogue of the tutoring session provides discourse scaffolds, such as questions and explanations, shown to be effective for learning in both classroom settings (Silliman & Wilkinson, 1994) and in vicarious learning (Craig, Brittingham, Williams, Cheney, & Gholson, 2009). In brief, the worked examples may be cognitively easier to learn from, but the tutoring sessions may provide more guidance and motivational benefits.

Although the choice between modeling with a worked example versus a tutoring session is clearly an important one that instructional designers and teachers must confront frequently, little research has been done on this issue. Early work on the dialogue versus monologue manipulation suggests that the choice can influence the learner's performance (Cox, McKendree, Tobin, Lee, & Mayes, 1999; Craig, Gholson, Ventura, Graesser, & the Tutoring Research Group, 2000; Driscoll et al., 2003; Fox Tree, 1999; Shebilske, Jordan, Goettl, & Paulus, 1998), which, in turn, suggests that the choice may influence learning. For example, Fox Tree (1999) found that performance was better while overhearing dialogues than while overhearing monologues. Fox Tree prepared materials for the experiment by dividing college students into pairs, called directors and matchers (Schober & Clark, 1989). The goal was for the director to describe an ordered set of abstract shapes (tangrams) to the matcher, so that the matcher could place the shapes in the same order as the director's pictures. Directors either gave instructions for the matcher to follow (monologue condition) or conversed freely with the matcher (dialogue condition). The sessions were recorded, and only those sessions in which matchers correctly ordered the tangrams were used as materials in the experiment. The results were that the participants who overheard dialogues outperformed those who overheard monologues on assembly tasks. The dependent measures reflected performance only (e.g., number of tangrams placed correctly) and not learning gains.

Observing tutoring has been compared with tutoring itself. Although these studies do not directly address our research question, they do indicate some factors that constrain the design of our experiment. In several experiments, Craig and colleagues (Craig et al., 2004; Craig, Sullins, Witherspoon, & Gholson, 2006) contrasted pretest to posttest gains of learners on 12 computer literacy topics. The learners either interacted directly with an intelligent tutoring system, AutoTutor (Graesser et al., 2004; Graesser, Jeon, & Dufty, 2008; Graesser, Person, Harter, & the Tutoring Research Group, 2001) or observed recordings of those tutoring sessions. Whereas learners in both conditions showed significant learning gains from pretest to posttest, participants in the computer tutoring condition significantly outperformed those in the observing tutoring condition in two experiments, with effect sizes of $d = .50$ in Study 1 and $d = .84$ in Study 2 (Craig et al., 2004). In two other experiments, there were nonsignificant trends in the same direction (Craig et al., 2006). This suggests that although computer tutoring can be more effective than observation, more testing is required to fully understand the factors impacting this finding.

Studies of learning from printed examples have shown that some students self-explain the examples and learn a great deal, whereas others read the examples in a passive way and learn considerably less (Chi, Bassok, Lewis, Reiman, & Glaser, 1989). This suggests that some observers in the Craig et al. studies may have watched the videos in a passive way that would reduce their learning.

In order to increase the number of observers using more active learning strategies, the Craig et al. (2004, Experiment 2) study was designed so that students would observe the videos in pairs. In this study, 110 participants were divided into three groups. The first two groups implemented the same computer tutoring condition ($n = 28$) and observing tutoring condition ($n = 28$) as in the other experiments. The third group consisted of pairs ($n = 27$ pairs) who observed the videos together. That is, 2 participants sat together in front of a computer monitor and watched a video of a tutoring session. They were encouraged to pause the video and talk to each other about information they did not understand in the video. Their conversation was audio recorded. All training conditions averaged about 35 min. The new condition produced gains that were intermediate between those of the tutoring condition and those of the individual observers of tutoring condition. However, the gains of the pairs in the observing tutoring condition were not significantly different from those of the two old conditions (individuals observing tutoring and tutoring).

Chi et al. (2008) compared human tutoring with observation of human tutoring along with several other control conditions. Their experiment was different from the Craig et al. (2004) experiments in several ways. First, Chi et al. used an expert tutor working face-to-face with a tutee. Second, in order to encourage equal amounts of activity, students in all conditions solved problems. The tutees solved problems with an expert tutor as a source of help. Other students solved problems with either videos of tutoring sessions or a textbook as their source of help. Third, the experiment contained five conditions: tutoring plus a 2×2 manipulation of collaboration (individual vs. pair) and source of help (textbook vs. video of tutoring sessions). Chi et al. coined the term *collaboratively observing tutoring* to refer to the condition in which pairs of students solved problems while observing a tutoring session.

The term reflects the combination of collaborative peer problem solving with observation of tutoring.

First, 10 expert tutoring sessions were conducted and video recorded. Then the other four conditions were run. Participants solved problems on paper, either individually or with a partner. While they solved problems, participants had access to either the textbook that they had studied during pretraining or to a video of the tutor and tutee solving the same problems as one they were trying to solve. Although the pairs studied together, they were assessed individually at pretest and posttest.

Chi et al. (2008) hypothesized that the combination of problem solving and collaborative problem solving would drastically reduce the frequency of passive observation of the videos and thus make collaboratively observing tutoring just as effective as face-to-face human tutoring. The predicted null effect was found. Although the number of students per condition was small ($n = 10$ for tutoring; $n = 20$ for collaboratively observing tutoring), there were statistically reliable advantages of the two conditions over the other three conditions that had similar cell sizes ($n = 20$ for pairs collaborating with a textbook; $n = 10$ for individuals observing tutoring; $n = 10$ for individuals with a textbook). These results suggest accepting the null result at face value. That is, one of the best forms of instruction known, face-to-face expert human tutoring, is no better than pairs of students solving problems while observing a video of the same problems being solved by a tutee and tutor. This intriguing result calls for further investigation and inspired the study reported here.

Taking the Craig et al. (2004) and Chi et al. (2008) studies together, one can infer a constraint on subsequent experimentation. Simply having pairs watch a video apparently does not reduce passivity nearly as much as having pairs solve a problem while they watch the tutor and the tutee solve the problem. This was confirmed in a follow-up analysis of audio recordings of the Craig et al. Experiment 2, in which pairs had an average of three conversational turns per session, with an average session lasting 35 min, whereas the collaborative observers in the Chi et al. study produced, on average, 121 conversational turns per 35-min interval. The increased level of collaboration was most likely due to the task demands of the study. Although the Craig et al. study did not require learners to perform any task other than watching the video, learners in the Chi et al. study performed a problem-solving task while observing tutoring.

Chi et al. (2008) also found that the tutoring videos were differentially effective. The observers learned more from some videos than from others. Chi et al. divided tutees into high and low pretest score groups. The pretest occurred after the pretraining and thus was partially a measure of the students' ability to learn physics. The 10 collaborative observers who viewed high-ability tutees videos learned significantly more than the 10 collaborative observers who viewed the low-ability tutee videos. This result suggests a recommendation for future experiments, specifically, the use of videos of high-ability tutees, as they somehow enhance the learning of the observers.

These studies (Chi et al., 2008; Craig et al., 2004) provide important guidelines about how to maximize *active observing* (Chi et al., 2008; Gholson & Craig, 2006) during tutoring. *Active observing* is described as observing that facilitates engagement with the materials so as to encourage deeper processing. First, observers should solve problems as they observe the video. Second, they should do so in pairs rather than working alone. And third, videos of high-ability tutees (i.e., students who have some knowledge of the material) should be used as the materials.

However, it should also be pointed out that the third most effective condition in the Chi et al. study (2008) was that of pairs collaboratively solving problems, with only a textbook as a source of help. Indeed on some measures, this group's gains were statistically equivalent to those of the top two groups (the tutees and the collaborative observers of tutoring). These gains occurred despite the fact that the textbook did not have worked examples based on the problems that the students were solving. Thus, if a pair got stuck, the pair might not have been able to find enough information in the textbook to resolve their impasse. On the other hand, if a pair in the collaboratively observing tutoring condition got stuck, they could always search the video to find out what the tutor sanctioned and resolve their impasse. Although the textbook and the tutoring videos were content equivalent in an abstract sense, the textbook lacked critical details that students might find useful when trying to solve problems and learn.

This suggested repeating the Chi et al. (2008) comparisons while controlling for the details of the content. Our experiment did so by using two kinds of videos. Both showed the same problems being solved with the same steps. However, some videos showed tutees working with a tutor to solve the problems, and the other videos showed an expert solving the problems and explaining the steps as he went. This ensured that the domain content was nearly identical. The difference in content was affective, metacognitive, and interactional. The expert-produced worked example was affect neutral, included no discussion or demonstrations of learning strategies, and, of course, contained no interaction with another person. The tutoring sessions included variations in affect, typically from the tutee; some demonstration of good and poor learning strategies (e.g., guessing, asking in-depth questions of the tutor) by the tutee; and considerable interaction between the tutor and tutee. In fact, there are probably many other differences between the two types of videos than the ones listed here. However, considerable future research is needed to identify these and to determine whether they are responsible for the learning differences we observed.

If the content in tutoring videos does increase students' active observing (e.g., interest, motivation, etc.), then pairs observing tutoring will learn more than pairs observing worked examples. By contrast, if detailed domain content is the key determinant of learning, then these two conditions should be equivalent in their effects on learning. If this null effect is observed, however, we would not know if it was due to equivalent learning or a flaw in the experimental method (e.g., low power). Thus, we needed to include a third condition to ensure that the method was working properly. For the third condition, we chose to have individuals solve problems while observing worked examples of the same problems being solved by an expert. Many studies have demonstrated high learning gains when individuals study worked examples and solve problems in various combinations (Atkinson et al., 2000; Renkl, 2005). Because Chi et al. (2008) found that learning of pairs observing tutoring matched that of actual tutoring, and as it is widely believed that tutoring is more effective than individual study of examples and problem solving (VanLehn, 2009), we expected that our target group, that is, pairs observing tutoring, would gain more than a control group consisting of individuals observing worked examples.

The Current Study

The LearnLabs (www.learnlab.org) of the Pittsburgh Science of Learning Center (PSLC) acted as facilitators for the investigation, bringing researchers together with schools and teachers to scientifically test learning theories in classrooms. The current study was conducted in the PSLC's Physics LearnLab. This LearnLab consists of introductory physics courses at the United States Naval Academy. These courses use the Andes system (VanLehn et al., 2005) provided by the PSLC as the homework portion of their course.

The Andes system provides introductory college-level physics homework problems. The Andes program is not a complete instructional system but rather a coach that helps the student solve homework problems. It plays the same role in the course as a workbook, except that it provides immediate feedback and hints while students are solving problems. It encourages certain problem-solving practices (e.g., drawing vectors instead of imagining them) to increase conceptual understanding of physics. The problem solving involves algebra, trigonometry, and vectors, but not calculus. In this way, it is intended to be used with almost any course's textbook, lectures, and labs. The system tracks the student's progress and provides him or her with a score based on the student's problem solving for each problem. As previous research on vicarious learning has shown the Andes system to be able to promote both procedural learning (Fox Tree, 1999) and deeper conceptual learning (Chi et al., 2008; Craig et al., 2006), it provides an ideal bridge for moving into the classroom. Andes is freely available on the Internet.[1]

In the study reported here, we evaluated collaboratively observing tutoring in the classroom. In doing so, we compared collaborative observers of tutoring videos during problem solving in Andes (collaboratively observing tutoring condition) against two control conditions. The first control condition required pairs of students to collaboratively observe a worked example video during problem solving in Andes (collaboratively observing examples condition). In the second control condition, individually observing examples, individual students viewed worked example videos alone while problem solving in Andes. Because the Andes system provides video explanations for the learners on select problems, this control was analogous to the help that was normally provided to the student in the course. Neither Chi et al. (2008) nor Craig et al. (2004, 2006) found learning gains for individuals who observed tutoring when compared with various controls. Therefore, the condition in which individuals observed tutoring was not taken into the classroom so as to avoid exposing students to an ineffectual learning condition.

Two contrasting hypotheses were tested in this design. The *active observing hypothesis* predicted that the learners in the collaboratively observing tutoring condition would outperform those in other conditions because of the highly dynamic tutoring session. Thus, the tutoring videos contained dialogue features (e.g., turn taking, pauses, and affect) and expert tutoring elements (e.g., corrections and scaffolding) designed to promote more active engagement with the video material. In contrast, the passive information display from the worked examples did not include such features. This hypothesis generated prediction of the following pattern of learning gains:

Collaboratively observing tutoring

$$> \text{collaboratively observing worked examples}$$
$$= \text{individually observing worked examples.} \qquad (1)$$

An alternative hypothesis, the *content equivalency hypothesis*, is based on the premise that the content is what really matters. If learners receive equivalent content, the method in which the material is presented should not influence learning (Klahr & Nigam, 2004). As all participants in our study were exposed to the same content, this hypothesis predicted the following pattern of learning gains:

Collaboratively observing tutoring

$$= \text{collaboratively observing worked examples}$$
$$= \text{individually observing worked examples.} \qquad (2)$$

Method

Participants

United States Naval Academy (USNA) students (ages 18–19 years; $N = 67$) from three sections of the PSLC Physics LearnLab participated in this study. Participation in the study was a mandatory learning experience integrated into the laboratory section of the class, but students' data were used in the study only with their consent. Just one student did not give consent. This resulted in an n of 10 for the individually observing examples condition, an n of 26 for the collaboratively observing examples condition, and an n of 30 for the collaboratively observing tutoring condition. Four participants did not complete any homework problems and were excluded from the long-term assessments. This left an n of 9 in the individually observing examples condition, an n of 25 in the collaboratively observing examples condition, and an n of 28 in the collaboratively observing tutoring condition.

Because of the nature of classroom research, the number of participants tends to be a fixed small number, which can lead to statistical power problems. In the original Chi et al. (2008) data, the observed effect size of collaboratively observing tutoring was large ($d = .97$) when compared with individually observing tutoring controls. A power analysis (Cohen, 1988) with the large effect size indicated the need for a total of 60 participants to reach a standard $\beta = .80$ level for power with $\alpha = .05$. On the basis of this power analysis conducted with the G*Power system (Faul, 2008), the limited sample size was deemed to be sufficient.

Materials

Andes tutoring system. The Andes tutoring system (VanLehn et al., 2005) provides introductory college level physics homework problems (see Figure 1). The system was selected for use in this study because it was integrated into the Physics LearnLab sections of the USNA's introductory physics courses as the homework for

[1] See http://www.andestutor.org/ for further details on the Andes system.

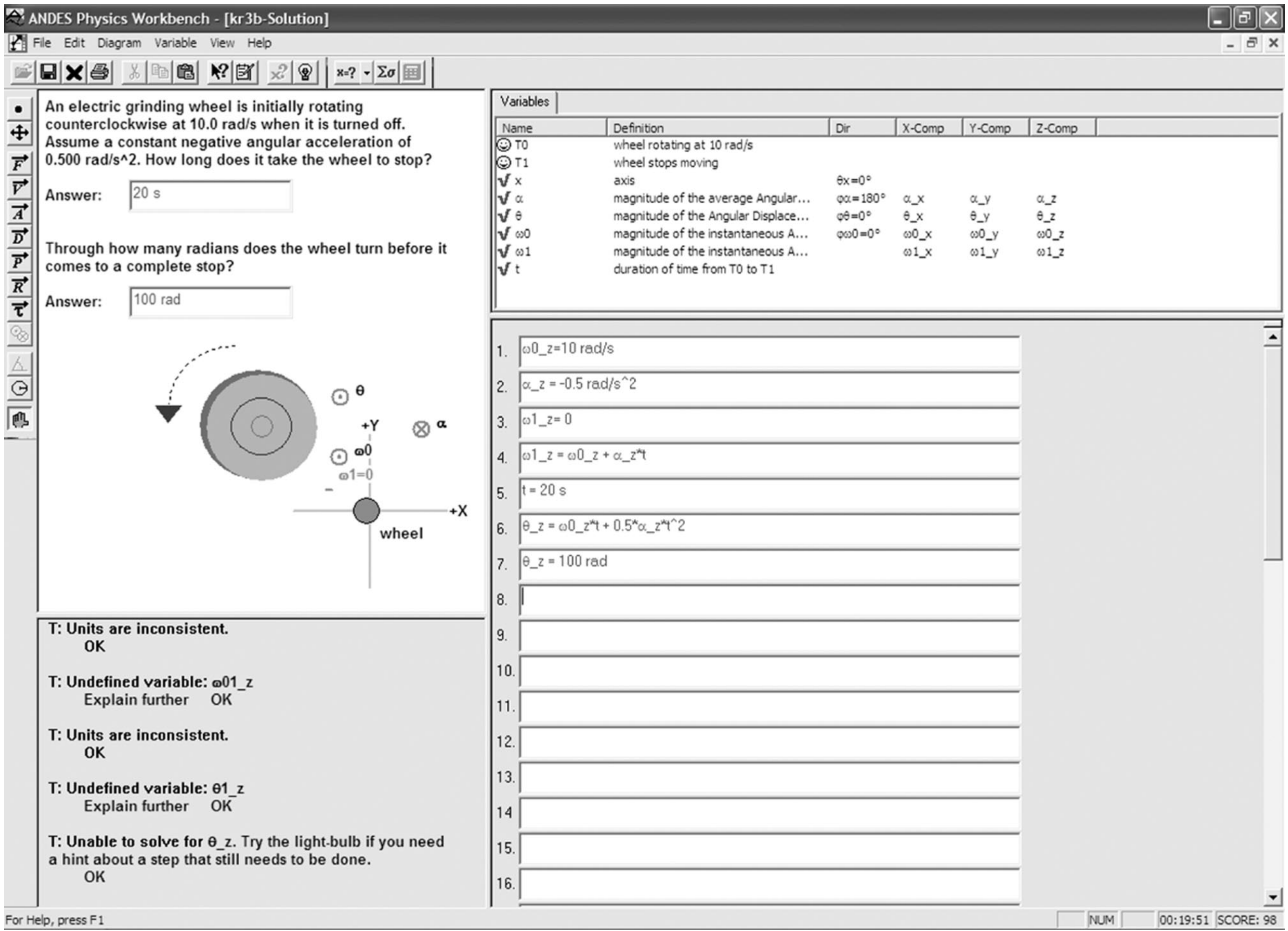

Figure 1. Screen shot of the Andes Physics Tutoring System with one of the two training problems on rotational kinematics.

the course. In addition to homework, the system was implemented as both the context of the learning videos and the problem-solving domain for training. However, because the study investigated the effect of observing videos, the help and feedback functions were disabled during the in-class training. The fully functioning version of Andes was available to students while they solved the course homework and on immediate post-training assessments.

Learning materials. Two sets of videos were observed by the learners. The videos were informationally equivalent in that they covered the same problem-solving steps in the same order and gave the same conceptual information. The TechSmith Camtasia® studio software package (TechSmith, 2006) was used to capture and edit all videos.

One set of videos consisted of an expert working out solutions for two Andes problems on rotational kinematics. There were two videos, one for each problem. In these videos, the expert, a retired USNA professor of physics with a PhD in the subject, solved two Andes problems while verbally presenting the relevant conceptual knowledge for each step. The videos presented the actions performed on the screen along with the expert's voice. In these videos, the expert covered the same steps in the same order as were covered in the tutoring session described below. Both sets of videos were approximately 22 min long.

The second set of videos consisted of recordings of an expert tutoring session on rotational kinematics. For these videos, the same physics expert tutored an intermediate-level tutee who had completed an introductory physics course that included rotational kinematics but did not have a degree or advanced training in physics. Again there were two videos, one for each problem. The videos were recorded by the same method as the worked example and displayed screen activity with voices of both the tutor and the tutee. The tutoring videos for the experiment were selected from a pool of five tutoring sessions on the basis of voice quality, the tutee's pretest being above 50% correct, the posttest score being above 90% correct, and complete topic coverage.

Immediate learning measures. Two isomorphic multiple-choice tests were used as pretest and immediate posttests. Both tests consisted of 12 four-choice questions assessing conceptual knowledge of rotational kinematics. The tests were counterbalanced across participants to prevent order effects.

In addition, three Andes problems were used as immediate posttest competency measures. The problems were designed as near-transfer problems using the same knowledge as in the training problems (see Appendix). The help and feedback features of the Andes system were available while participants completed the near-transfer problems. The Andes scoring rubric (VanLehn et al.,

2005) subtracted points for errors and overuse of help. Students were familiar with the scoring rubric as it was used for their homework.

Long-term retention and transfer. The long-term measures consisted of the students' Andes homework scores. They were instructed to complete these homework problems at any point between when they were assigned and the section test. Assignment of the homework problems occurred after the training session was completed.

The homework problems were divided into three categories. There was one long-term retention problem, three long-term near-transfer problems, and three long-term far-transfer problems. The long-term retention problem was one of the two problems taught during training. The homework problems listed by category can be found in the Appendix.

Equipment. During the training phase, participants shared a laptop computer with two Belkin headphone splitters that allowed for two headsets and microphones to be used on the same machine by the 2 participants. Participants' on-screen problem-solving activity and verbal interactions during training were captured using the TechSmith Camtasia recorder (TechSmith, 2006).

Design and Procedure

The current in vivo study implemented a pretest–posttest design with a long-term classroom impact measure to determine differences among the three experimental groups: collaboratively observing tutoring condition, collaboratively observing examples condition, and individually observing examples condition. The USNA students were randomly assigned to one of three conditions by lab tables. Thus, whereas they were allowed to work with their normal lab partner, they were blind to the condition of their lab table until after they selected their table. Following assignment of conditions, participants provided informed consent; any questions about the procedure were answered by the experimenter. Because this was a classroom setting with the instructor present, participants were given the option of contacting the experimenter outside of class if they wished to be excluded from the study.

After the informed consent process, all participants watched a brief 4-min video. This video introduced them to the terms and basic concepts of rotation to ensure that they had the prerequisite knowledge for completion of their problem-solving task. Afterward, all participants individually completed the multiple-choice pretest.

The learners then performed the training task, which consisted of completing two Andes problems with the aid of video solutions for each problem. They solved rotational kinematics problems using the Andes tutoring system while simultaneously watching either the tutoring session or the worked example videos showing the same problems being solved. Their voice and onscreen problem-solving activity were recorded.

All participants worked at their own pace on this task. However, there was no significant difference in the amount of time groups worked on the training problems, $F(2, 60) = 0.53$, $p = .59$ (for individually observing worked examples, $M = 32$ min; for collaboratively observing worked examples, $M = 28$ min; and for collaboratively observing tutoring, $M = 29$ min).

The students were assessed individually immediately after training with a multiple-choice posttest and three immediate near-transfer problems performed in Andes on rotational kinematics. Once the participants indicated they were done with the training session, each participant was given a multiple-choice posttest, which he or she completed individually. After the participant finished the multiple-choice test, the experimenter administered the Andes problems, which each participant also completed individually. Participants were given as much time as they needed to complete these tasks. All participants finished before the end of the class period.

Andes homework data. Long-term measures consisted of Andes homework problems that students completed in an unsupervised setting (their dorm rooms, typically). On average, the students completed their homework 26 days after the training session; there were no significant differences for time delays among groups. The 26-day delay might seem excessive, but it was in line with participants' completion of other physics homework problems. This delay was due to a standard class deadline set by the instructor. Completion of homework for the current section being covered was not requested until the end of the section. This resulted in most homework being completed on a fairly delayed basis.

Although the instructor encouraged students to help each other, students were required to solve their own Andes problems. The instructor was adept at using log data to detect cases where one student copied another's homework, so this rarely happened. Log data were harvested from the PSLC DataShop, which routinely collects Andes log data as the students do their homework.

Students could access the hints available in the Andes program and were permitted to consult their textbook, their friends, and even the instructor as they completed their homework. The long-term measures served as a type of dynamic assessment (Bransford & Schwartz, 1999; Haywood & Tzuriel, 2002), measuring the students' ability to transfer their learning to authentic instructional situations rather than operating within the sequestered setting of standard tests.

Andes homework was scored by an automatic metric that gave participants credit for correct steps while solving the problem and deducting points for errors and help requests. A total of 100 possible points per problem could be earned. The participant's average Andes score was calculated for each category and reported with the average total possible score of 100. If a participant did not complete any homework problems, he or she was excluded from this data set.

Results and Discussion

Immediate Learning Measures

Multiple-choice data. A series of analyses of variance (ANOVAs) was performed on the learners' multiple-choice data from the immediate pretests and posttests. The ANOVA performed on pretest data did not reveal significant differences among groups. Whereas the multiple-choice test showed that all students gained significantly from pretest to posttest, $F(1, 65) = 14.99$, $p < .001$, $\eta^2 = .231$, there were no significant differences among conditions on learning gains with the multiple-choice data, $F(1, 63) = 0.13$, $p = .877$, $\eta^2 = .003$. That is, the collaborative observers of tutoring, the collaborative observers of worked examples, and the individual observers of worked examples all seem to have learned the same amount according to the multiple-choice data. Means and standard deviations for pretest and posttest data for all conditions are given in Table 1.

Immediate near-transfer data. An ANOVA was performed on the average Andes score across the three Andes near-transfer problems that were given immediately after the training (see Table 1 for Andes score means and standard deviations). As with the multiple-choice data, there were no significant differences among conditions, $F(1, 63) = 0.25$, $p = .782$, $\eta^2 = .001$. This lack of significance among conditions in the immediate learning data is consistent with the content equivalence hypothesis.

Long-Term Learning Measures

Long-term retention data. An ANOVA was performed on the participants' long-term retention data to determine differences among groups. This analysis revealed a significant difference between conditions, $F(2, 59) = 3.44$, $p < .05$, $\eta^2 = .104$. We performed a priori orthogonal contrasts to test our predictions. These tests revealed that students in the collaboratively observing worked examples condition did not significantly differ from students in our individually observing worked examples condition on their long-term retention tests, $t(59) = 0.67$, $p = .503$. Students in the collaboratively observing tutoring condition were then compared with the combined participants of the individually observing worked examples condition and the collaboratively observing worked examples condition. This contrast was significant and in favor of participants in the collaboratively observing tutoring condition, $t(59) = 2.61$, $p < .05$, $d = .68$. See Table 2 for means, standard deviations, and standard errors for long-term retention data.

Additionally, the mean time to solve the retention problem was 548.39 s (approximately 9 min). This is significantly longer than the 293.29 s (approximately 5 min) per Andes physics problem during the immediate posttest, $F(1, 62) = 21.85$, $p < .001$, $h^2 = 0.358$. This significant time difference provides some confirmation for our interpretation that students took the long-term retention problem and other homework problems much more seriously than the immediate posttest problems in that participants spent more time attempting to solve each problem. However, this is only an assumption of ours given the data provided. It does not rule out possibilities that observing tutoring led students to perform other beneficial behaviors, such as seeking help from instructors or discussing problems with other students. Future work should include follow-up surveys or interviews to determine the specific mechanisms that produced this effect.

Long-term near-transfer data. We conducted an ANOVA on the participants' near-transfer data to determine differences among groups. This analysis revealed a significant effect of condition, $F(2, 59) = 4.39$, $p < .05$, $\eta^2 = .129$. We again performed a priori contrasts to test our predictions. These tests revealed that once again, in the near-transfer data, participants in the collaboratively observing worked examples condition were not significantly different from those in the individually observing worked examples condition, $t(59) = 0.21$, $p = .834$. The students' data from the collaboratively observing tutoring condition were then compared with the students' data of the combined individually observing worked examples and collaboratively observing worked examples conditions. This contrast was significant in favor of participants in the collaboratively observing tutoring condition, $t(59) = 2.85$, $p < .01$, $d = .74$. See Table 2 for means, standard deviations, and standard errors for the learners' near-transfer data.

Long-term far-transfer data. We conducted an ANOVA on the participants' far-transfer data to determine differences among groups. This analysis revealed a significant effect of condition, $F(2, 59) = 4.89$, $p < .05$, $\eta^2 = .142$. We conducted a priori contrasts to test our predictions. These tests revealed that participants in the collaboratively observing worked examples condition were not significantly different from our individually observing worked examples condition, $t(59) = 0.05$, $p = .963$. We then compared the students' data from the collaboratively observing tutoring condition with the data from the combined individually observing worked examples and the collaboratively observing worked examples conditions. This contrast was significant in favor of participants in the collaboratively observing tutoring condition, $t(59) = 2.96$, $p < .05$, $d = .77$. See Table 2 for means, standard deviations, and standard errors for far-transfer data.

As can be seen in Table 2, we observed a different pattern of data between our immediate learning measures and long-term learning measures. No group differences were observed in our immediate learning measures. In our long-term learning measures, collaboratively observing tutoring outperformed both individually and collaboratively observing examples. Although the results of our long-term data argue strongly in favor of our active observing hypothesis, the null effect on immediate assessment is consistent with the content equivalency hypothesis. The observed reversal in effects could be due to two possible factors. First, the students

Table 1
Means and Standard Deviations for Immediate Learning Measures for the Three Conditions

Condition	Multiple-choice pretest *M*	Multiple-choice pretest *SD*	Multiple-choice posttest *M*	Multiple-choice posttest *SD*	Gain scores *M*	Gain scores *SD*	Immediate near transfer *M*	Immediate near transfer *SD*
Individually observing worked examples	.58	.23	.69	.18	.11	.20	64	22
Collaboratively observing worked examples	.56	.22	.65	.20	.09	.20	61	29
Collaboratively observing tutoring	.58	.18	.66	.17	.08	.16	57	30

Note. Values shown are proportion correct on multiple-choice pretest problems, proportion correct on multiple-choice posttest problems, proportion gain scores (scores on multiple-choice posttest minus scores on multiple-choice pretest), and immediate near-transfer score (Andes problem-solving score; out of a possible 100).

Table 2
Means, Standard Deviations, and Standard Errors for Long-Term (Robust) Learning Measures From Andes Homework Scores Across the Three Conditions

	Long-term retention			Long-term near transfer			Long-term far transfer		
Condition	*M*	*SD*	*SE*	*M*	*SD*	*SE*	*M*	*SD*	*SE*
Individually observing worked examples	73	17	6	68	33	11	53	42	14
Collaboratively observing worked examples	78	22	4	70	30	6	54	31	6
Collaboratively observing tutoring	88	13	2	88	13	2	77	22	4

Note. Andes homework scores are out of a possible 100 points.

might have taken the long-term assessment more seriously than the immediate tests. This could be attributable to the homework being part of the students' course grade. Thus, we assume that because the students likely took this series of Andes problems more seriously, we were able to detect an effect for our manipulations.

Alternatively, the immediate assessments may tap only shallow knowledge, which is provided equally well by all three conditions. For instance, all three types of instruction might have allowed students to remember the problem-solving steps immediately afterwards and then to use them for a copy-and-edit style of problem solving (VanLehn, 1998) but not to gain the deeper understanding that is needed for long-term performance and transfer.

Analysis of Students' Behavior During the Process of Collaboratively Observing

In order to test the claims of the active learning hypothesis, we analyzed the students' problem-solving behavior during training to determine some potential causes of the differences between the two collaboratively observing conditions. The videos were analyzed at both a macro level and a micro level.

At the macro level, the pairs' interactions were coded on the basis of their task engagement levels. In these codings, two raters viewed 30-s excerpts from each pair's recorded session. These excerpts were taken at 10% intervals from each collaborative observer session (e.g. at 3 min, at 6 min, and so forth for a 30-min video). This resulted in a total of 10 selections per video, for a total of 450 codings conducted. Active engagement was coded when the collaborative pair was discussing the problem-solving task (planning), engaging in discussion to determine a discrepancy in a member's knowledge, engaging in explanation of a problem-solving step, or collaboratively engaged in the problem-solving task. A kappa score of .76 was obtained between the two coders. This kappa level was deemed a sufficient level of agreement (Cohen, 1960), and disagreements were worked out between raters. A *t* test conducted on the data from the engagement coding revealed that the pairs who collaboratively observed tutoring were more actively engaged in their problem-solving task than the pairs who collaboratively observed an example, $t(44) = 2.13$, $p < .05$, $d = 0.63$. See Table 3 for the mean proportion of time that collaborative learners in each group were actively engaged.

This pattern was replicated to a lesser extent in a microlevel analysis of each pair's problem-solving steps. Each step of the problem was coded on the basis of the way in which it was obtained by the collaborative pair. Steps could be copied directly from the video example or generated by the collaborative pair. Further, we examined whether the observing pairs were using the videos to help scaffold learning by coding whether the video was searched when attempting to solve a step. While the observed copying, $t(43) = 0.45$, *ns*, and generating, $t(43) = 0.51$, *ns*, behaviors were not significantly different across conditions, pairs observing tutoring did actively search the video more often when attempting to solve a step, $t(43) = 2.09$, $p < .05$. Pairs of learners observing tutoring were more likely to search the video to verify a step in the solution and not just to copy it. Thus, these learners were more likely to find discrepancies between their internal mental model and that presented in the video. This discrepancy detection is a key component of active learning (Chi, de Leew, Chiu, & LaVancher, 1994; Wittrock, 1989). See Table 3 for the means and standard deviations of the codings by condition.

Table 3
Means and Standard Deviations for Active Engagement Levels (Proportion) and Active Search as Well as Means and Standard Deviations for the Proportion of Problem-Solving Steps That Collaborative Observers Either Copied or Generated

	Active engagement		Active search		Copied steps		Generated steps	
Condition	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Collaboratively observing worked examples	.48	.19	.00	.00	.30	.32	.68	.30
Collaboratively observing tutoring	.60	.19	.09	.20	.27	.23	.72	.23

Note. Values for active engagement and active search, respectively, are based on proportion of time during collaboration and active searching of video during problem solving.

General Discussion

The overall pattern of data partially supports our active observing hypothesis. Although immediate assessments of competence showed no differences across conditions, students in the collaboratively observing tutoring condition outperformed the students in the other conditions for all three of our long-term learning measures. Further, as claimed by the active learning hypothesis, learners in the collaboratively observing tutoring group displayed more active learning processes, with both more active engagement and active searching of the material during training.

These results suggest that when students collaboratively observe tutoring, they tend to have more active collaboration, which is followed by increases on long-term learning measures. This finding provides more evidence that active learning can improve learning from observing (Chi et al., 2008; Gholson & Craig, 2006) and is consistent with the literature on self-explanation (Chi et al., 1989) and multimedia learning (Mayer, 2001; Wittrock, 1989) that indicates the importance of active learning for deeper conceptual learning or transfer of learning to occur. More important, this finding shows that collaboratively observing tutoring while problem solving is a useful tool for improving learning outcomes in classroom settings when compared with traditional worked examples.

The current research was conducted in physics problem solving. Future research is required to test the generalizability of this finding to other domains, to younger populations, and to classroom instruction. However, past research has shown that vicarious learning techniques with a scripted question-led dialogue between a virtual tutor and tutee is effective for teaching 8th- to 11th-grade students (Craig et al., 2008; Gholson et al., in press). Vicarious learning has also been shown to be effective in the domains of conceptual physics (Gholson et al., in press), the circulatory system (Craig et al., 2008), and computer literacy (Craig et al., 2006; Gholson et al., in press). It is feasible that collaboratively observing tutoring would be a viable learning method in these areas as well.

Given the consistent findings of our long-term data and analyses of training transcripts, the null results on our immediate measures may be a result of some students rushing through the assessments perhaps because these assessments, unlike the long-term ones, did not affect the course grades. However, this explanation is not the only one possible. For instance, collaboratively observing tutoring might lead to later changes in student study behavior. That is, watching the tutee on the video struggle but ultimately learn might encourage students to study harder themselves.

However, the difference of our immediate low stakes versus our long-term high stakes assessments in classrooms settings could be a warning to researchers in the Learning Sciences as they move laboratory research into the classroom. Students in the laboratory are volunteers that usually receive compensation for their participation in the form of money or course credit. This compensation is often proportional to the time they work. This may create a demand to take all of the tasks seriously. On the other hand, students who perform tasks as part of their normal instruction, even if they have consented to have their data used by experimenters, may apply their normal prioritization schemes. In our case, students might have felt that after they received the instruction offered that day (e.g., observing the videos while solving problems), they could finish learning rotational kinematics at home and thus might have viewed the posttesting as merely an untimely nuisance. However, follow-up experiments are needed to verify this claim.

Because observing tutoring involves pairs of students watching a tutoring video together while collaboratively solving problems, it is most easily deployed as a classroom activity provided that each pair has a computer or a video player that the students can control. However, collaborative viewing could also be useful as a homework activity if a pair of students can meet after school or can collaborate remotely. The success of tutoring observation also suggests the utility of taking another look at standard instructional practice, wherein the teacher tutors a student in front of the class.

The current study suggests that observing tutoring is an effective alternative to standard instructional methods such as studying worked examples. Other laboratory research suggests that tutoring observation is as effective as interacting with both a human tutor (Chi et al., 2008) and an intelligent tutoring system (Craig et al., 2006). This study is the first to test observing tutoring in vivo, that is, as part of normal class instruction. Although the classroom context appears to have affected our assessments immediately after training, the instruction itself seems to have survived the transition from laboratory to a real classroom while retaining its effectiveness. If these results continue to replicate in the classroom, then we would have an effective alternative to labor-intensive human tutoring and costly intelligent tutoring systems.

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Appendix

Andes Tutoring System Training and Assessment Items

Andes Training Problems (Andes Label: KR1A, KR3B)

1. A wheel is rotating counterclockwise as a constant angular velocity of π rad/s. through what angle does the wheel rotate in 60.0 s?

2. An electric grinding wheel is initially rotating counterclockwise as 10.9 rad/s when it is turned off. Assume a constant negative angular acceleration of 0.500 rad/s^2. How long does it take the wheel to stop? Through how many radians does the wheel turn before it comes to a complete stop?

Andes Immediate Near-Transfer Problems (Andes Labels: KR1C, KR3C, KR4B)

1. A wheel rotates counterclockwise at a constant angular velocity of 2.5 rad/s. How long does it take the wheel to rotate through an angle of 210 rad?

2. The magnitude of the initial angular velocity of a wheel rotating counterclockwise is 30 rad/s. If the wheel takes 15 s to slow to a complete stop, what was the average angular acceleration of the wheel?

3. A wheel is initially at rest. If the wheel undergoes an average angular acceleration of 1.5 rad/s^2 over time, how fast would it be rotating 10 seconds later?
angular velocity:
After this time, the wheel continues to rotate at constant angular velocity.
What is the angular displacement of the wheel during a subsequent 20 second time interval?
angular displacement:

Andes Long-Term Retention Problem (Andes Label: KR1A)[A1]

1. A wheel is rotating counterclockwise at a constant angular velocity of π rad/s. through what angle does the wheel rotate in 60.0 s?

Andes Long-Term Near-Transfer Problems (Andes Labels: KR1B, KR2B, KR3A)

1. A wheel is rotating clockwise at a constant angular velocity of 3*π rad/s. What is the magnitude of the angular displacement of the wheel after 45.0 seconds?

2. The initial angular velocity of a wheel is π rad/s in a clockwise direction. If the wheel is speeding up with a constant angular acceleration of π/4 rad/s^2, what is the magnitude of the angular velocity of the wheel after 15.0 seconds?

3. The magnitude of the initial angular velocity of a wheel rotating counterclockwise is π rad/s. If the wheel is slowing down with an average angular acceleration of π/6 rad/s^2, how long does it take to stop?

Andes Long-Term Far-Transfer Problems (Andes Labels: KR4A, KR6A, and KR7A)

1. A wheel has an initial angular velocity of 3*π rad/s in a counterclockwise direction. If the wheel is slowing down with a constant angular acceleration of π/4 rad/s^2, through what angle does it turn before it reaches a final angular velocity of π rad/s in a clockwise direction?

2. Two fixed pulleys are attached by a fan belt. The radius of the first pulley is 0.030 m. The magnitude of its angular velocity is 2*π rad/s in a counterclockwise direction. If the radius of the second pulley is 0.020 m, what is the magnitude of its angular velocity if the fan belt does not slip?
Note: Consider rim1 and rim2 to be points on the rims of the pulleys in contact with the belt at the instant depicted. Use a relative position vector to represent the perpendicular distance of a rim point from the axis of rotation.

3. A wheel is rotating at a constant angular velocity of π rad/s in a clockwise direction. The radius of the wheel is 0.030 m. What is the magnitude of the linear velocity of a point halfway between the center of the axle and the outside edge of the wheel?
Note: use a relative position vector to represent the perpendicular distance of a rotating point from the axle.

Note. An asterisk within the Andes problems represents the multiplicative function.

[A1] Whereas Problem KR3B (along with Problem KR1A) was initially intended to be used as a long-tern retention problem, researchers had no control over the course content, and this problem was not assigned as homework by the instructor.

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