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Observing Tutorial Dialogues Collaboratively: Insights About Human Tutoring Effectiveness From Vicarious Learning

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Abstract

The goals of this study are to evaluate a relatively novel learning environment, as well as to seek greater understanding of why human tutoring is so effective. This alternative learning environment consists of pairs of students collaboratively observing a videotape of another student being tutored. Comparing this collaboratively observing environment to four other instructional methods—one-on-one human tutoring, observing tutoring individually, collaborating without observing, and studying alone—the results showed that students learned to solve physics problems just as effectively from observing tutoring collaboratively as the tutees who were being tutored individually. We explain the effectiveness of this learning environment by postulating that such a situation encourages learners to become active and constructive observers through interactions with a peer. In essence, collaboratively observing combines the benefit of tutoring with the benefit of collaborating. The learning outcomes of the tutees and the collaborative observers, along with the tutoring dialogues, were used to further evaluate three hypotheses explaining why human tutoring is an effective learning method. Detailed analyses of the protocols at several grain sizes suggest that tutoring is effective when tutees are independently or jointly constructing knowledge: with the tutor, but not when the tutor independently conveys knowledge.

Keywords: Learning from observing; Tutoring; Learning from tutoring; Learning from collaborating; Human tutorial dialogue; Physics; Problem solving; Vicarious learning

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1. Introduction

Although learning of subject matter domains can occur with conventional methods of instruction that are based on a transmission view of learning, much recent work has focused on instruction based on a more constructivist view of learning. The two most widely studied and implemented methods are human tutoring and collaborating with a peer. Compared to learning in a traditional classroom, learning from face-to-face human tutoring is extremely beneficial and has the largest effect size, ranging from 0.4 to 2.0 (Bloom, 1984; Cohen, Kulik, & Kulik, 1982), followed by learning from collaborating with a peer, with a substantially smaller effect size, ranging from 0.21 to 0.88 (Johnson & Johnson, 1992; Slavin, 1990). Studies that have directly compared interacting with a tutor (or experimenter) with collaborating in pairs have also found tutoring to be more effective than collaborating (Pilkington & Parker-Jones, 1996). Besides these two widely studied methods, many other creative methods of learning are being explored, such as learning by observing (McKendree, Stenning, Mayes, Lee, & Cox, 1998) and learning by teaching an animated agent (Biswas, Schwartz, Leelawong, Vye, & TAG-V, 2005; Schwartz, Blair, Biswas, Leelawong, & Davis, 2007).

Although human tutoring is extremely effective, it is not cost effective to scale up. Current usage of human tutoring in schools tends to be pull-out systems that are available to only a few students. Developing intelligent tutoring systems is also costly and difficult to implement, although substantial progress is being made (e.g., by the Pittsburgh Science of Learning Center).

The research reported in this article has both a theoretical and a pragmatic goal. The theoretical goal is to gain further understanding of why face-to-face human tutoring is so effective. Better understanding of how tutoring is effective will help improve designs for intelligent tutoring systems (ITSs) as well as prescribe designs for alternative learning environments that might be more easily developed, implemented, and scaled up. The pragmatic goal of this research is to test such an alternative learning environment, one that leverages the advantages of learning from tutoring and collaborating, with learning from observing, into a single learning environment. Very little research has explored the effectiveness of learning from observing another student learn; moreover, the results have been inconsistent. We propose an explanation that can not only account for the discrepant results in the literature but can also serve as a method to optimize the effectiveness of learning from observing. We refer to this potential explanation as the *active/constructive/interactive observing hypothesis*, and it refers to how actively engaged and constructive the observers are. This hypothesis is derived more generally from our earlier finding that being constructive facilitates learning, the general self-explaining effect (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Chi, de Leeuw, Chiu, & Lavancher, 1994).

This article begins by analyzing the tasks and reinterpreting the results from the learning from observing literature. Then the article introduces our active/constructive/interactive observing hypothesis and describes our pragmatic goal, which is to test the effectiveness of an alternative learning environment by comparing it with four other learning methods. We then explore our theoretical goal by elaborating three tutoring hypotheses and seek support for these hypotheses with in-depth analyses of the tutoring protocols. In order to gain further understanding of tutoring effectiveness, we examine learning from both the

perspective of the tutees as well as the perspective of the observers. The article concludes with a discussion of the conditions under which learning from tutoring and learning by observing tutoring can be successful and ways in which tutoring can be usefully expanded and scaled up.

2. Learning from observing

There is currently somewhat of a discrepancy in the literature with respect to the benefit of learning from observing. We start by defining how observational learning has been investigated and then address the discrepancy issue.

We use the very neutral terms *learning from observing* or *learning vicariously* to encompass learning contexts that include both watching someone else learn (*watching* refers to observing visual inputs) and overhearing the ensuing dialogues between a learner and an instructor (*overhearing* refers to observing auditory inputs). Aside from the distinction between *watching* and *overhearing*, another important distinction that needs to be made is between learning from observing someone else *learn* and learning from observing someone else *act or behave*.

Learning from observing *actions* or *behavior* has been explored fairly extensively in at least three or four different areas of research. In social psychology, for example, studies have been undertaken to see how one learns from watching someone act aggressively (Bandura, 1969, 1986). In these cases, it is not necessary for the persons we watched to have exhibited learning (i.e., they were not learning to act less aggressively); they merely have exhibited some actions from which we the observers might learn. In short, they are the actors and we are watching them model some behavior. The role of discourse is often not explicitly addressed in such cases because much of this work focuses on physical skills (thus, the overhearing component of observing is absent). By and large, highly effective learning of physical skills does take place by watching overt behavior of individual actors, even without exposure to discourse (i.e., without overhearing).

Learning from observing modeling has also been studied in work settings (Latham & Saari, 1979) and on-the-job apprenticeship learning. More recently, learning from observing actions has been studied with renewed interests by neuroscientists and developmental psychologists, termed *imitative learning*. Imitative learning is an ability that is uniquely human and not available to primates, in the form that requires the observer, such as a child, to transform and take on the perspectives of others (Meltzoff, 2005). Imitative learning is assumed to play an important role underlying the preservation of cultural practices (Meltzoff, 2005; Tomasello, 1999).

It is not totally surprising that one can learn from observing physical skills, since the actions underlying physical skills can be overtly modeled, in a more or less one-to-one correspondence. For example, knitting consists of making loops that can be modeled in a step-by-step way in terms of the direction and sequencing of the knitting needles (although the pattern or the design must be planned ahead), so one would predict that an observer can learn to knit by watching all the intervening steps.

But can one learn from observing mental or cognitive skills? Cognitive skills can include both learning skills (such as self-explaining, asking questions) and other task-specific skills

(such as problem-solving). A few recent studies have shown that one can also learn learning skills from observing. For example, students can learn to ask questions by observing (watching and overhearing) an animated agent ask questions (Craig, Gholson, Ventura, Graesser, & the Tutoring Research Group, 2000) or learn to collaborate by observing others collaborate (Rummel & Spada, 2005).

There are two important characteristics to note about learning these learning skills from observing. One characteristic is that the observers were not expected to learn the content of the articulations made by the actors. For example, the observers in the Rummel and Spada (2005) study were not expected to learn the diagnosis of the panic disorder case. Rather, the goal was to learn the skill of collaboration. A second characteristic is that the actors themselves were not learning. For example, the animated agent in the Craig et al. (2000) study was not learning. In short, in these two studies, the observers were learning the learning skills of asking questions and collaborating, rather than learning the content of the questions asked by the animated agent or the topic of the collaborative diagnosis. Thus, the question remains as to whether one can learn the content of cognitive skills (or task-specific skills such as problem-solving) from observing.

In Chi and Bjork (1991), we had argued that task-specific cognitive skills that involve a many-to-one mapping between the processing steps and the observable overt outputs might be much more difficult to learn from watching. For instance, when an expert or teacher solves a math or physics problem on the board, if we watch only the overt actions alone (such as writing equations), then the number of equations written does not correspond to the complexity of the underlying reasoning steps. One solution to overcoming the many-to-one correspondence between the covert reasoning steps and the overt actions of solving complex problems is to have the expert externalize her thinking or make her thinking visible by giving explanations in a monologue mode (Collins, Brown, & Holum, 1991). This would add an overhearing component. However, making thinking visible does not overcome the dual problems that (a) experts are notorious for not being able to express all their thinking because much of their knowledge is tacit (Nisbett & Wilson, 1977) and (b) even if the experts could express their thinking elaborately as in giving monologue didactic-like explanations, it is becoming increasingly clear that students do not learn very well from hearing such explanations (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001; VanLehn, Siler, Murray, Yamauchi, & Baggett, 2003). For example, we already know that listening to an instructor, an expert, or a peer giving monologue explanations is less facilitating to learning when compared to many other ways, such as listening to dialogues (Driscoll et al., 2003; Fox Tree, 1999), being scaffolded (Chi et al., 2001), or having the students self-generate explanations (Chi et al., 1989; Webb, 1989) or self-generate questions (King, 1992).

To conclude, however, that complex cognitive tasks may not be learnable from observation, even if experts make their thinking visible in an explanatory monologue mode, may have been premature because it is possible that one can learn from observing if the observers can overhear not the monologue but the dialogue between a learner and an actor/instructor. For example, instead of watching just one actor explaining and modeling a task-specific cognitive skill (such as a teacher explaining and solving a problem out loud), can observers learn by watching and overhearing the dialogue between a teacher and a student? In fact, this would be a situation in which an observer is observing someone else learn. McKendree et al. (1998)

and Stenning et al. (1999) assume that access to dialogue is a critical component to learning vicariously. Two conditions in Cox, McKendree, Tobin, Lee, and Mayes' (1999) study tested this assumption. They compared learning materials created by tutor-tutee dialogue (in which a novice student constructed tree diagrams with the help of an expert), captured as a movie and shown to observers, with learning materials consisting of only animation of the tree diagramming. Observers performed better when they watched a movie and overheard tutor-tutee dialogue than watching only an animation of diagramming, in which there was no verbal communication. Thus, an observer could learn to diagram from watching and overhearing more so than just from watching, suggesting that overhearing is a critical component of learning from observing.

However, an earlier study by Schober and Clark (1989) seems to suggest the opposite conclusion. In the Schober and Clark (1989) study, the overhearers heard recordings of dialogues between pairs of participants in which one participant (analogous to a tutor) described the sequencing of 16 tangram figures and the other participant (analogous to a tutee) had to order them as instructed. Each overhearer's task was also to sequence the tangrams. The result was that the overhearers could not sequence them as accurately as the tutees who could converse with the tutor. Schober and Clark's conclusion was that understanding can only be built up by participating in dialogues, in which the participants could jointly build their common ground. Accessing dialogues from overhearing was argued to be not as effective as participating in dialogues.

At first glance, Cox et al.'s (1999) results seem to contradict the findings of Schober and Clark (1989) with respect to the benefit of overhearing dialogues in vicarious learning. However, the two studies are actually incomparable. In the Cox et al. (1999) study, they were comparing two conditions of observing: watching plus overhearing versus just watching. Not surprisingly, watching plus overhearing is better than watching alone, as recommended by the "making thinking visible" approach to instruction (Collins et al., 1991). The Schober and Clark (1989) study, on the other hand, compared the conditions of participating (or interacting with a tutor) versus observing such interactions. Moreover, the former study measured learning, whereas the latter study did not.

The Schober and Clark assumption, that only by participating in interactions can mutual understanding evolve, is also supported in the results of Craig, Driscoll, and Gholson (2004) and Craig, Sullins, Witherspoon, and Gholson (2006). Across four experiments on learning, comparing interacting with a virtual tutor versus observing such interactions that were captured on video files (thus the observing included both watching and overhearing), they found that students interacting with a virtual tutor produced greater learning effects from pre- to posttest than observing such interactions. In two of the experiments, the differences were significant, and in two other experiments, the differences were not significant, although in the same direction. Based on these preliminary findings, averaging across their four experiments gives us an effect size of 1.78 for interacting with a tutor and 1.12 for observing such interactions. In short, interacting with a tutor seems to be a more effective form of learning than observing such interactions.

In sum, judging from the difference in the relative magnitude of these effect sizes as well as the effect sizes reported in the literature on tutoring (ranging from 0.4 to 2.0) and collaborating (from 0.21 to 0.88), we can tentatively conclude that learning task-specific cognitive skills

from observing is possible when the observers have access to dialogues (with an estimated effect size of 1.12), although it appears to be less effective than learning from participating in tutoring but perhaps more effective than learning from collaborating.

3. The active/constructive/interactive observing hypothesis and an alternative learning environment

If learning from observing is in fact not as effective as learning from being tutored, is there a way to optimize learning from observing to make it comparable to the level of learning from tutoring? Essentially, the results in the literature suggest that interacting with a tutor is better than watching and overhearing. But is it interacting with a tutor that is important for learning or interaction per se? In all the studies cited above, the observers were observing individually with no opportunity to be interactive, so that they may or may not be actively engaged. Could the observers learn more if they had opportunities to be active or constructive or interactive? In this article, these three terms will be used interchangeably and loosely. (More specific definitions, the underlying processes, and discriminations among the three terms—active, constructive, interactive—will be spelled out in a forthcoming paper.)

We tested our active/constructive/interactive observing hypothesis in a pilot study by encouraging individual overhearers to be actively engaged and constructive by requiring that they self-explain while overhearing an audiotaped recording of a tutor giving instructions to a tutee on how to put together a portion of an AM radio kit (Chi, McGregor, & Hausmann, 2000). The design was essentially a replication of the Schober and Clark (1989) study but used a different task and required the overhearers to be active. The overhearers' success in putting together the radio kit was compared to a tutee group who received the same instruction but could interact directly with the tutor by asking questions. There were no significant differences in performance between the two groups. This null effect is consistent with our active/constructive/interactive observing hypothesis, suggesting that the difficulties sometimes encountered by overhearers may be attributed to their passive stance. Thus, the results in the literature showing the better performance of the participants who interacted with a tutor than participants who merely observed such interactions may be explained by the lack of opportunities to actively interact per se and not necessarily interacting with a tutor.

To further test our hypothesis, the present study implemented an alternative learning environment that involved giving the observers opportunities to interact not with a tutor but with a peer. This environment consisted of having pairs of students collaboratively observe another student (a tutee) being tutored on how to solve a problem while simultaneously solving the same problem that is being tutored. It is essentially the same design as the Schober and Clark (1989) study, with the exceptions that pairs of students collaboratively observed while solving a problem, and learning gains were measured. This learning environment essentially capitalizes on the benefits of learning from tutoring and collaborating, in the context of learning from observing someone else learn. Learning in this target condition—observing tutoring collaboratively—is contrasted with learning from tutoring, collaborating, observing alone, and studying alone. We hope to provide direct evidence for the benefit or non-benefit of

this alternative vicarious learning environment, thus testing the active/constructive/interactive observing hypothesis.

3.1. Method

3.1.1. Participants

One highly experienced teacher was selected to serve as a tutor in this study. This Tutor (henceforth capitalized to refer explicitly to him) possessed a Ph.D. degree in physics and had taught university-level physics for over 30 years. Moreover, this Tutor is a member of the Andes tutoring project (VanLehn et al., 2005) in which he acted as the in-house domain expert. Therefore, he is somewhat familiar with the research issues, such as knowing the benefit of encouraging students to be constructive. We intentionally used a single tutor in order to examine the effect of tutee variability.

In addition to our Tutor, 70 undergraduates from the University of Pittsburgh participated as paid volunteers. Ten of these undergraduates participated in the tutoring condition (henceforth referred to as the Tutees). The remaining 60 participants were assigned to four non-tutoring conditions. Each participant or pairs of participants in the non-tutoring conditions were yoked to one Tutee by gender so that an equal number of male and female participated in each condition. Unfortunately, due to this yoking procedure, complete random assignment to condition was not possible because we had to collect the tutoring data before collecting data from the remaining conditions. Furthermore, participation in the tutoring condition required the Tutees to consent to allowing their videotapes to be shown to other participants in two of the conditions. Consequently, participants were assigned to the tutoring condition before being randomly assigned to the remaining conditions.

All student participants were selected to have had taken at least one physics course at the high school level, but no physics courses at the college level. Prior to the study, each participant listed all the physics courses they had taken in high school and the grade(s) they received. There were no differences among conditions in either the number of courses taken or in their self-reported grades.

3.1.2. Materials

The problem-solving domain is quantitative kinematics, based on the materials in chapter 5 of the classic physics textbook *Fundamentals of Physics* (Halliday & Resnick, 1981), dealing with the application of Newton's three laws of motion to problem situations (e.g., a block on an inclined plane, two blocks joined by a string supported by a pulley). Three kinds of problems were used in this study. The pretest and posttest problems were used for assessment, and the tutoring problems were used in the intervention.

The pretest consisted of four problems selected by the Tutor from the back of chapter 5 that covered the major concepts and principles, such as weight force, normal force, compound body, tension, mass, acceleration, and Newton's three laws of motion. The easiest problem served as a warm-up problem. These four pretest problems are shown in the first column of Appendix A. The appendix in its entirety can be found at <http://www.cogsci.rip.edu/CSJarchive/Supplemental/Index.html>.

For tutoring, the Tutor designed five problems that incorporated the same set of concepts and principles as were used in the pretest. These tutoring problems (consisting of a warm-up problem and Problems 1–4), ordered by level of difficulty, with the Tutor's rationale for constructing them, and their correspondences to the pre- and posttest problems, are shown in the middle column of Appendix A.

For the posttest, the experimenters designed four problems that roughly corresponded to Problems 1–3 of the pretest and Problems 1–4 of the tutoring problems. (See Problems 1, 2, 3, and 4 in the posttest column of Appendix A). Problems 1–3 in the pretest and posttest had identical problem situations (e.g., an inclined plane problem where the goal is to find tension), but they may differ in the values of the variables (i.e., for the angle, the forces, the masses), and some of the posttest problems have additional question parts. But essentially the deep structures of the problems were similar, in terms of what principles to apply (Chi, Feltovich, & Glaser, 1981). Problem 4 on the posttest did not correspond to any problem in the pretest. Because Problem 4 was so difficult that no student solved any parts of it correctly, this posttest Problem 4 was eliminated from further analyses.

Besides the physics text, the assessment, and tutoring problems, 10 videotapes were also created from the tutoring sessions of the Tutor with each of the 10 Tutees. Each videotape consisted of the Tutor tutoring a Tutee on the warm-up and two of the four tutoring problems. The average duration of the videotapes was 79.86 minutes.

3.1.2.1. Scoring of the posttest problems: The Tutor was asked to provide worked-out solution steps to the pretest and posttest problems. A step is a written or spoken solution line, often an equation, reflecting a component of the problem-solving procedure, such as finding tension by applying Newton's second law. Each step can be differentiated as either *shallow* or *deep*. A shallow step reflected computation and the use of convention or notation, and a deep step required the application of physics concepts and principles.

Each step in solving the corresponding pretest and posttest problem types was then compared. Some steps were repeated in both the pre- and the posttests and these will be referred to as *matched*, and other steps were *unique* to solving either the pretest or the posttest problems. A breakdown of the number of matched and unique steps can be found in Table 1. The majority of unique steps in the posttest were embedded in additional questions posed in parts b and c of a problem. There were a few unique steps in the pretest because the pretest was actual problems selected from the textbook, whereas the posttest problems were constructed in such a way as to optimize assessment of learning from the tutored problems.

3.1.2.2. Problem-solving models: The Tutor was also asked to explain how to solve each of the tutoring problems he constructed. His transcribed verbal protocol was used

Table 1
The number of matched and unique shallow and deep steps

	Shallow Steps	Deep Steps	Total
Matched on pre- and posttest	6	16	22
Unique to pretest	2	3	5
Unique to posttest	3	6	9

to create models of how to solve each of the tutoring problems in terms of problem-solving nodes, as shown in Fig. 1 (for tutoring Problem 2). Each node corresponded to a state in a problem space. These models were later used to code and score the tutoring protocols.

3.1.3. Design

The design for this study consisted of five conditions: the benchmark tutoring condition, the target observing collaboratively condition, and three others conditions that served as various controls. In the tutoring condition, each Tutee interacted individually with the same Tutor to solve three tutoring problems (the warm-up plus 2 of the 4 tutoring problems, chosen by the Tutor). Exactly which of the two tutoring problems were used with each Tutee varied across Tutees, as the selection was left to the Tutor's discretion. (Giving the Tutor a choice of problems was intended to mimic an authentic tutoring situation.) To ensure that the same set of problems was solved an equal number of times across all conditions, each participant or pair of participants in the other four conditions were yoked to one of the Tutees in the tutoring condition.

In the observing collaboratively condition, each pair of participants (henceforth referred to as Collaborative Observers) watched a videotape of one of the tutoring sessions and together they tried to solve the same three problems as were being solved by the Tutee in the tutoring tape. In the collaborating condition, each pair of participants (henceforth referred to as Collaborators) solved one set of three problems (yoked to a Tutee set) collaboratively with no exposure to tutoring, but they were given access to the physics text from which they had studied chapters 1–5. Thus, while this condition allowed for interaction with a peer, it controlled for the effects of observing tutoring. In the observing alone condition, each participant (Lone Observer) watched a videotape of one of the tutoring sessions individually and tried to solve the same problems as were being solved in the tutoring tape. Finally, in the studying alone condition, each participant (Solo Solver) tried to solve three problems (again yoked to a Tutee set) with the text available as a resource. Table 2 summarizes the five conditions, the number of participants in each condition, the learning resources available to each condition, and the learning activities in which the participants could engage in, besides solving problems.

Table 2
Learning resources and learning activities of the five conditions

	No. of Participants	Learning Resource	Learning Activity
Tutoring	$n = 10$	Human tutor	Interacting in dialogue and being tutored
Observing collaboratively	$n = 20$	Peer and videotape	Interacting in dialogue and observing
Collaborating	$n = 20$	Peer and text	Interacting in dialogue and reading
Observing alone	$n = 10$	Videotape	Observing
Studying alone	$n = 10$	Text	Reading

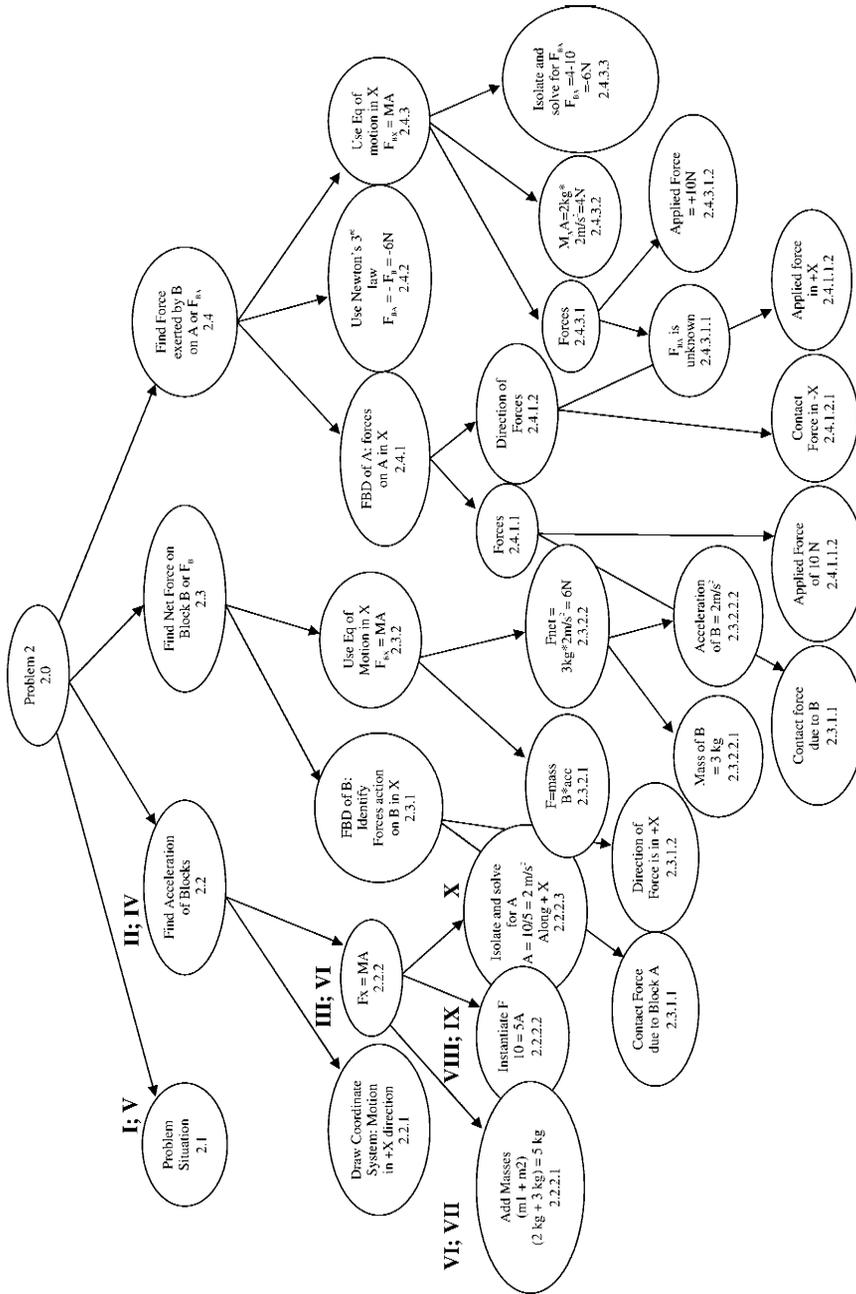


Fig. 1. Model of problem-solving nodes for the compound body problem (Problem 2).

3.1.4. Procedure

Following the procedure of our earlier work (Chi et al., 1989), the experiment consisted of four distinct phases for all conditions: background (chapters 1–4), chapter 5 plus pretest, intervention, and posttest. During the first background phase, each participant studied the first four chapters of Halliday and Resnick (1981), covering basic background knowledge such as units of measurement, vectors, velocity as it relates to motion in one dimension, concepts of force and mass, as well as how these concepts relate to acceleration. Participants had to learn these first four chapters individually in our lab to a criterion level, defined as attaining a score of at least 80% correct on a preselected subset of problems and questions from the end of each chapter. If they failed to achieve this standard, they were told which problems were wrong and were then required to restudy the materials and re-solve the problems until they met the criterion. This background phase took on average 6.34 hours to complete (ranging from 6.22 to 6.55), occurring over several sessions. There were no significant overall or pair-wise differences between conditions on this measure.

After attaining mastery of chapters 1–4, the participants individually studied all of chapter 5 in the second phase. Then they were asked to solve the pretest problems, with the text available to them, in order to reduce stress and mimic a more authentic learning context. No feedback was given on the correctness of their solutions to the pretest problems, nor were they required to reach any criterion. Thus, the pretest assessed how well students could learn chapter 5 materials on their own, having presumably mastered the prior (chapters 1–4) knowledge to the same degree (80% criterion).

The first 10 participants who were recruited and had completed the pretest were assigned to the Tutoring condition. Then the remaining 60 participants were randomly assigned to the other four treatment conditions for the third phase.

All problem-solving took place on a large whiteboard so that we could capture on videotape an accurate record of all ongoing problem-solving activity. For all five conditions, the participants were audio- and videotaped. The Tutor was encouraged to keep the sessions to approximately one and one-half hours in length.

The Collaborative Observers were given one of the tutoring tapes to watch on a large television along with the same three problems to solve. They were also required to perform their problem-solving on a whiteboard, with each member using a different colored marker. The Collaborative Observers were further told that they may discuss the videotape and their understanding of the materials at any time, and that they could stop, rewind, or fast forward any section of the tape. Allowing the participants to manipulate the tape in this way mimics potential authentic learning situations involving videotapes (such as a virtual or real classroom).

The Collaborators were given a set of three problems to solve along with a copy of chapters 1–5 from the Halliday and Resnick (1981) text. The Collaborators were encouraged to discuss and help each other solve the problems while working on a whiteboard.

The Lone Observers condition received similar instructions to those in the observing collaboratively condition. Rather than being encouraged to work with a partner (since they had no partners), the Lone Observers were told that they could talk out loud whenever it felt natural to do so, and they could stop, pause, forward, or rewind the tutoring tape.

Finally, the Solo Solvers were given instructions similar to the collaborating condition with the exception that they would work alone. Like the Lone Observers, the Solo Solvers were also instructed that they could talk aloud whenever it felt natural to do so.

All participants were informed that the purpose of this (intervention) phase was to learn how to solve kinematics problems and that their understanding and ability to individually solve similar kinematics problems would be assessed later with new problems. They were also told to limit their problem-solving time to 2 hours.

After the intervention, each participant took the posttest individually, without access to the text, with an average delay of 7.4 days (ranging from 6.0 to 8.3 days). There were no significant differences between groups on this measure of delay. Thus, the posttest measured long-term learning and retention. Each student was given unlimited time to solve all four of the posttest problems.

3.2. Learning results

The analyses in this section compare the learning performance for all five conditions and explore other contrasts to either test the active/constructive/interactive observing hypothesis or to set the stage for additional analyses to test the tutoring hypotheses in the second half of this article.

3.2.1. Learning from the pretest to the posttest

Pretest and posttest problem-solving solutions were scored in terms of the steps as described in the Method section. Recall that a step could be shallow or deep and matched or unique. Learning from the pretest to the posttest can be analyzed as an analysis of covariance (ANCOVA), using all the matched and unique posttest steps as the dependent variable and all the matched and unique pretest steps as the covariate. Alternatively, learning from pretest to posttest can be analyzed as an analysis of variance (ANOVA), using the gain scores on the matched steps only. We will report both analyses, beginning with the ANCOVA using all the matched and unique steps for shallow and deep knowledge separately and then provide reasons for why the remaining analyses throughout the rest of the article focus only on the matched deep steps.

3.2.1.1. Analyses of covariance for all shallow steps: Recall that all the participants in all the conditions had access to the textbook during the pretest but not the posttest. This means that performance on the shallow steps may be enhanced at the pretest, since they could copy the equations and notations correctly from the text. Consequently, it is important that we analyze shallow and deep steps separately. Accordingly, an ANCOVA was carried out, using all 9 of the matched and unique posttest shallow steps while controlling for all 8 matched and unique pretest shallow steps. There were no significant differences across conditions in the proportion of shallow steps learned. The lack of differences among the conditions supports our interpretation that shallow steps, assessing the use of conventions, accuracy of calculations, and appropriate use of units, can be copied from the text during the pretest so that no substantial learning differences were detected from the pretest to the posttest. The average shallow posttest score, adjusted for pretest score, ranged from a low of 49% for the Tutees

to a high of 61% for the Solo Solvers. The lack of detectable differences in learning shallow knowledge suggests that the remaining analyses should focus only on deep steps.

3.2.1.2. Analyses of covariance for all deep steps: Using all 22 posttest matched and unique deep steps adjusted for all 19 pretest matched and unique deep steps, an ANCOVA shows that there were significant differences across conditions, $F(4, 64) = 2.596, p = .044$. Figure 2a shows the adjusted posttest means with standard error bars. However, there were no significant differences among the top three conditions: tutoring, observing collaboratively, and collaborating.

Although the top three conditions were statistically equivalent, their effect sizes, contrasting each with the most conventional studying alone condition as a control, show a systematic decrement, from tutoring (Cohen's $d = .815$), to observing collaboratively ($d = .613$), to collaborating ($d = .326$). Furthermore, these top three conditions were clearly better learning methods since the average of their adjusted posttest scores was significantly better than either observing alone ($F[1, 66] = 5.111, p = .026, d = .532$) or studying alone ($F[1, 66] = 6.448, p = .044, d = .522$).

3.2.1.3. Analysis of variance of matched deep steps: The preceding analyses using ANCOVA compromise our power because we have a small number of participants (we lose a degree of freedom). Hence, due to the availability of the text at the pretest thus contaminating the learning of shallow steps, and due to the loss of one degree of freedom when using ANCOVA, henceforth, analyses of variance, comparing pretest to posttest using matched deep steps only will be reported throughout this article.

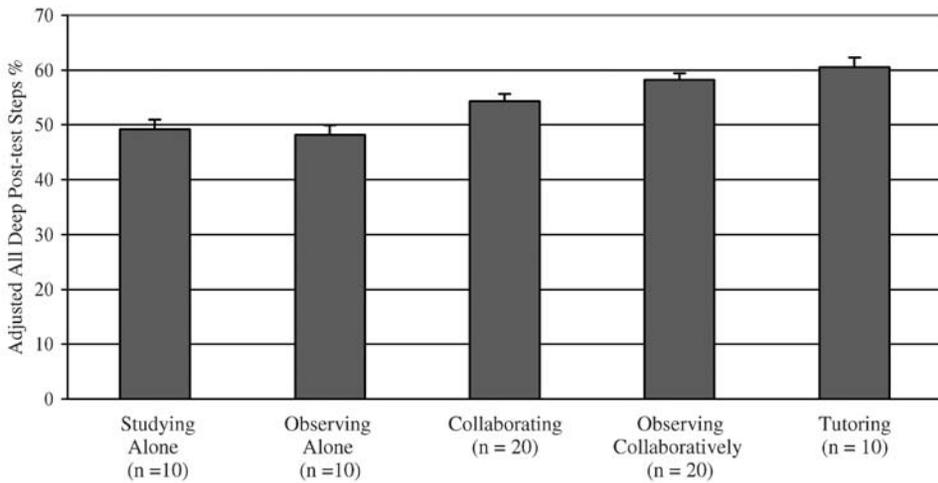
Fig. 2b shows the proportion and standard error bars of matched deep steps scored correctly on the pretest and posttest. There are five patterns of results to note. First, as in the ANCOVA for all deep steps (Fig. 2a), there was a significant overall difference in the gains across conditions for matched deep steps, $F(4, 65) = 3.787, p = .008$.

Second, the pre- to posttest gains were significant for only three of the five conditions: tutoring (21.3%, $F[1, 9] = 29.277, p = .0005$), observing collaboratively (17.03%, $F[1, 19] = 17.385, p = .001$) and collaborating (7.19%, $F[1, 19] = 7.432, p = .01$). The gains for observing alone (8.91%) and studying alone (3.39%) were not significant. The effectiveness of the top three conditions is consistent with the ANCOVA results reported above, showing that the top three conditions were equivalent and better than the other two conditions. One interpretation of this result is that the three significant conditions are the only ones involving active interaction by participation in dialogues, supporting the generality of the active/constructive/interactive hypothesis in that it is not restricted to the benefit of interactivity in a tutoring context.

Third, although the top three conditions were more similar to each other and provided significant learning, their effect sizes (expressed in terms of Cohen's d for the gains) descended from 1.063 for tutoring, to 0.883 for observing collaboratively, to 0.405 for collaborating, in the same ordering as the effect sizes of these three conditions in the ANCOVA of all deep steps, as well as the results in the literature. The effect sizes for observing alone and studying alone are 0.291 and 0.296, respectively.

Fourth, although the pre- to posttest gains were significant for all three conditions involving interactive dialogues as mentioned above, and descended from the tutoring to the

a)



b)

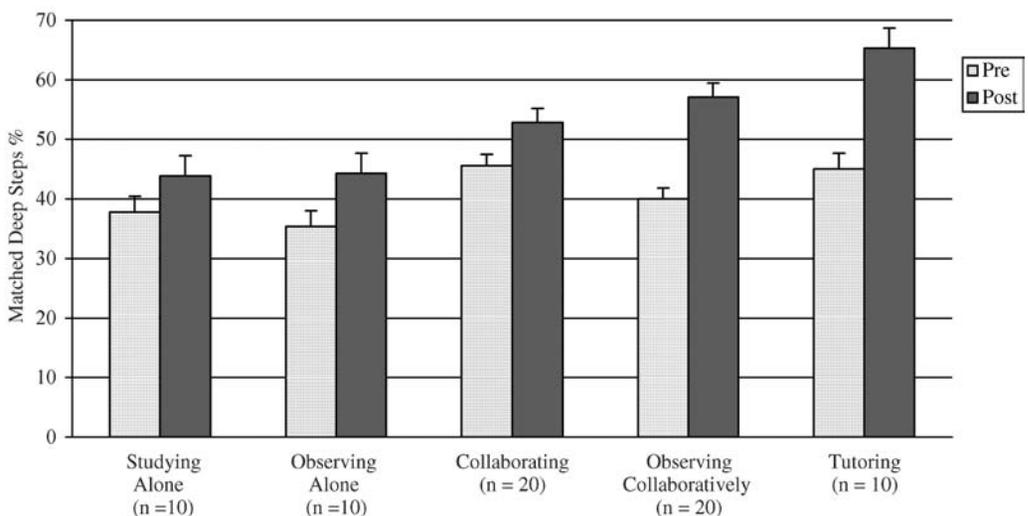


Fig. 2. (a) Adjusted mean proportion of all deep posttest steps, controlling for all deep pretest steps for each condition. (b) Mean proportion of pretest and posttest scores for matched deep steps for each condition.

collaborative observing to the collaborating condition, there was no significant difference between the top two conditions using ANOVA. The statistically equivalent gains of the two highest performing conditions—tutoring and observing collaboratively, is further validated in that the gains of these two conditions were significantly greater than the gains of all the other three conditions: collaborating, observing alone, and studying alone, $F(1, 67) = 6.927$, $p = .002$; $d = .556$. (Although the ANCOVA results show the top three conditions to be equivalent, whereas the ANOVA results show only the top two conditions to be equivalent,

it may be that the ANOVA results provide a more sensitive comparison given our small sample size.) This equivalence of the top two conditions shows that observing collaboratively is as effective a learning method as the gold standard of being tutored, supporting the active/constructive/interactive observing hypothesis in that it shows that observing can be as effective a way to learn as tutoring if the participants get opportunities to be active/constructive. One can be active/constructive by interacting with a peer and not necessarily with a tutor.

Finally, Observers who observed collaboratively had marginally greater learning gains than those who observed alone, $F(1, 65) = 3.842, p = .055; d = .425$. This contrast can be accounted for by the interactions between the paired participants afforded by the observing collaboratively condition as compared to the observing alone condition, thus directly supporting the active/constructive/interactive observing hypothesis.

3.2.2. Good versus poor tutees

The overall pretest scores of the Tutees were highly variable, suggesting that some Tutees independently learned more about the material covered in chapter 5 than other Tutees. Their pretest scores tended to cluster into two equal groups, with the top half showing much higher scores than the bottom half, $F(1, 8) = 13.94, p = .006, d = 2.360$. Therefore, the 10 Tutees could be divided into 5 Good and 5 Poor Tutees on the basis of a median split on their pretest scores. Because the pretest assessed what the Tutees have learned on their own from studying chapter 5, the pretest is not a measure of prior background knowledge because all Tutees had a similar lack of background knowledge in physics. Instead, the pretest is a measure of the Tutees' ability to learn without the intervention of the Tutor. Thus, the Tutees' pretest scores can be conceived of as an index of whether they were good or poor learners.

The Good and Poor Tutees' learning ability could be further differentiated in the time and errors in learning the materials prior to tutoring. Although not statistically significant, it did take the Poor Tutees more time ($M = 440.60$ minutes) to study chapters 1–5 than the Good Tutees ($M = 388.00$ minutes). Furthermore, even though all Tutees were trained on the first four chapters to a criterion of 80% on problem-solving, the Good Tutees did make significantly fewer errors ($M = 3.0$) than the Poor Tutees ($M = 6.2, F[1, 8] = 5.885, p = .041, d = .609$). In short, the Good Tutees were better learners, in terms of how much they could understand in a shorter amount of time.

Differences between the two groups can also be detected during tutoring. While being tutored, the Poor Tutees generated many more errors across all three tutoring problems on average ($M = 89.2$) than Good Tutees ($M = 55.8, F[1, 8] = 27.474, p = .001, d = 3.276$). Moreover, Poor Tutees expressed confusion twice as frequently ($M = 6.8$) as the Good Tutees ($M = 3.1, F[1, 8] = 17.551, p = .003, d = 2.644$). Being good learners translated to more learning as measured by the pre- to posttest gains. The Good Tutees had greater learning gains (24.6%) than the Poor Tutees (15.6%) on matched deep scores, $F(1, 8) = 9.502, p = .015, d = 1.976$.

Overall, these measures confirm the fact that a median split of Tutees on the basis of their pretest performance is a legitimate way to contrast more successful learners (the Good Tutees) with the less successful learners (the Poor Tutees). This contrast serves a useful purpose for subsequent analyses.

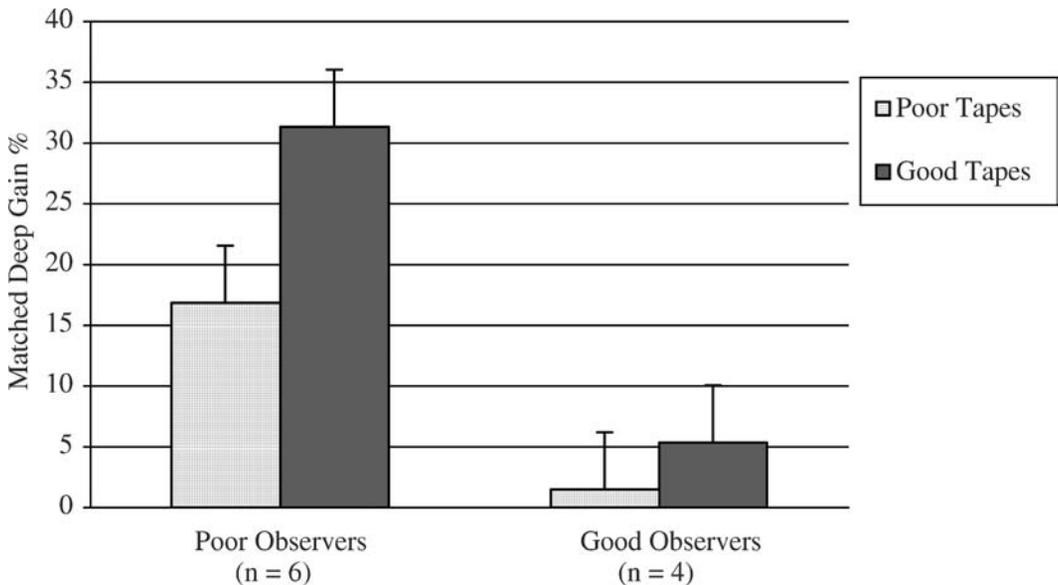


Fig. 3. Mean proportion of gain for matched deep steps for Good and Poor Collaborative Observers watching Good and Poor Tutee tapes.

3.2.3. Collaborative observers learn more from observing good versus poor tutees

The 10 Collaborative Observers who observed the 5 Good Tutees' tapes (henceforth referred to as the Good Tapes) learned substantially more ($M = 21.9\%$) than the 10 Collaborative Observers who observed the 5 Poor Tapes ($M = 7.8\%$; $F[1, 18] = 6.723, p = .018, d = 0.573$). In fact, the 21.9% gain of the Collaborative Observers of Good Tapes is comparable to (in fact slightly exceeds) the mean gain for the Tutees per se (21.3%).

The Collaborative Observers themselves can also be divided into Good and Poor Observers, based on a median split of their pretest scores. Although the Good Tapes were more effective than the Poor Tapes in general for both the Good and Poor Observers, the advantage of the Good Tape is much more pronounced for the Poor Observers (see Fig. 3). In fact, the Poor Observers ($n = 6$) benefited the most from observing the Good Tapes, in that they gained significantly more than the other three groups of Collaborative Observers combined ($n = 14, F[1, 18] = 6.907, p = .017, d = 1.153$). They gained on average 31.3%, which far exceeded the average gain of even the Good Tutees (24.6%). It does not appear as though the Good Observers were performing at ceiling given that they only scored 76% correct on the posttest. Hence, the Good Tapes were extremely effective for learning from observing, especially for Poor Observers. Despite the small sample sizes, this finding is extremely encouraging because it indicates the tremendous potential of providing good tapes for poor learners to observe.

3.2.4. More interactions facilitate learning from observing

Although this article is not about how the Observers learn per se (such analyses are being carried out and will be reported in a later paper), we can further test the

active/constructive/interactive observing hypothesis by showing that how interactive the Observers were is an important determinant of their learning. One simple way to measure how interactive the Collaborative Observers were with each other while watching the tapes is to compute the amount of substantive contributions (to be defined in the latter half of this article) made by each partner in their exchanges.

The Collaborative Observers did engage in a substantial amount of interaction producing in the range of 274–492 exchanges (except for an outlier pair who had only 22 exchanges). We computed the amount of interactions between each pair by the difference in the proportion of substantive contributions each partner made. A difference of less than 15% (with an average difference of 9.2%) was considered High Interactive Observers since both partners were contributing more equally to problem-solving, and there were 6 pairs of such dyads. The remaining four pairs had a difference of greater than 15% and can be considered disproportionately Low Interactive Observers. The High Interactive Observers learned significantly more ($M = 26\%$) than the Low Interactive Observers ($M = 4\%$, $F(1, 18) = 10.313$, $p = .005$, $d = 1.506$). Thus, this result further validates our active/constructive/interactive observing hypothesis.

3.2.5. Active lone observers

If being active/constructive/interactive is the key to learning, then another way to test this hypothesis is to see if we can tease apart those Lone Observers who were active versus those who were more passive. The active/constructive/interactive observing hypothesis predicts that the more active individuals would learn more. Accordingly, for the observing alone condition, 4 participants were identified as being more active in the following ways. Contrasting these 4 participants with the other 6, these active Lone Observers were more likely to write problem-solving steps on the whiteboard ($M = 74.00$ steps vs. $M = 7.33$); to manipulate the tutoring tape by pausing, rewinding, and fast-forwarding ($M = 29.75$ vs. $M = 19.33$); and to pose self-querying questions such as, “Mass A was cancelled. Are you sure you’re allowed to do that?” ($M = 7.5$ vs. $M = 0.2$).

Not surprisingly, these 4 active Lone Observers gained more (18.4%, from pretest to posttest on their matched deep step scores) than the 6 passive Lone Observers (2.6%), even though the two groups did not differ in terms of their pretest deep step scores (34.7 and 35.8%, respectively). Note that the 18.4% gain of the active Lone Observers is comparable to the average gains of the Tutees (21.3%) and the Collaborative Observers (17.0%). Moreover, the 2.6% average gain for the more passive Lone Observers was comparable to the gains of the Solo Solvers (3.4%). Even though the number of active Lone Observers is small, the differential gains comparing the active Lone Observers versus the passive Lone Observers lends further support to the active/constructive/interactive observing hypothesis.

3.3. Summary

The results reported in this section contrast the advantages of learning from being tutored, from vicariously observing tutoring (either collaboratively or alone), from collaborating, and from studying alone as our baseline control condition, since it mimics most closely what students can acquire without any help from either a tutor, a peer, or a videotape. There are several findings to note. First, our data from the tutoring, collaboratively observing,

and collaborating conditions replicate the evidence in the literature. As discussed in the Introduction, learning gains from tutoring typically have a larger effect size (.4–2.0) than those from observing collaboratively (1.12) and collaborating (.21–.88). The learning gain effect sizes we found, of 1.063 for tutoring, 0.883 for observing collaboratively, and 0.405 for collaborating, follow the same trend, and are significantly better than that of studying alone (effect size of 0.296). Note that the magnitude of our effect sizes reflects the fact that we are measuring learning of deep knowledge in a fairly difficult problem-solving domain.

Second, the literature is often discrepant on the learning effectiveness of observing vicariously, in the sense of learning from observing someone else learn. Our hypothesis, that the discrepancy in the literature may arise from how active/constructive/interactive an observer is, is supported in four ways. The first comparison that supports this active/constructive/interactive observing hypothesis is the equivalent learning gains of the Collaborative Observers and the Tutees. This null effect suggests that having and using the opportunity to interact with a peer is as effective as directly interacting with a tutor. The same interaction interpretation can also be offered for the second comparison, between the Collaborative Observers versus the Lone Observers. The better learning outcomes of the Collaborative Observers may have arisen from their having the opportunity to be more active and constructive by interacting with their partners. The third result that supports our hypothesis is the contrast between the more interactive Collaborative Observers and the less interactive Collaborative Observers. The more interactive ones learned more. The fourth comparison that supports our hypothesis can be gleaned from teasing apart those Lone Observers who were more active versus those who were more passive. The more active Lone Observers learned more.

In sum, these four findings support our active/constructive/interactive observing hypothesis, suggesting that collaboratively observing tutoring while solving problems may be an effective learning environment. Moreover, the greater gain of the active Lone Observers poses the plausible interpretation that the advantage of the three conditions in which students could participate in dialogues may not have to do with dialogues per se but rather that participating in dialogues is a natural forum for being more interactive and thus constructive.

Although we consider the studying alone condition to be one of our poorest baseline control condition, we should point out that this studying alone condition is analogous to what the literature has referred to as *learning by doing* (Anzai & Simon, 1979). Although learning by doing or problem-based learning has been promoted in the past as an optimal way to help students learn, especially in medical education, more recent evidence shows that learning by doing is not as effective as learning from studying worked-out examples (Sweller, van Merriënboer, & Paas, 1998), consistent with our comparisons showing that learning by doing is definitely not as effective as the top three conditions. Okita and Schwartz (2006) also have some intriguing evidence consistent with ours, showing that learning by doing (such as answering questions) is not as effective as learning by observing someone else answers questions.

Although our observing collaboratively learning environment is not novel, we have provided systematic data comparing it with other learning methods. For example, such a learning environment has been explored in a single case study by Frederiksen, Donin, Meilleur, Roy, and Bracewell (1999), but they did not contrast this learning environment with other learning environments to assess its benefit. Such a learning environment was also explored by Craig et al.

(2004). They compared learning from interacting with an animated tutor agent, with learning from either observing tutoring individually (Exp. 1) or collaboratively (Exp. 2). Although their tutoring condition was superior to their individual observing condition (consistent with our tutoring vs. observing alone contrast), their collaboratively observing condition was not significantly different from either their tutoring condition or their observing alone condition.

The discrepancy between the null results reported by Craig et al. (2004) in Exp. 2 (of no overall significant differences across their three conditions), and ours may be due to the fact that their collaborative observers interacted infrequently, on average 2.91 times per 35-minute tutoring session, whereas our Collaborative Observers interacted on average 15.36 episodes per 35-minute duration. Thus, being not as interactive may have weakened the learning gains of their collaborative observers, as the contrast in learning gains of our High Interactive and Low Interactive Collaborative Observers shows. Nevertheless, their results, even though not significant, could be viewed as compatible with ours. The effect sizes for their tutoring (2.06) was similar to the effect size for their collaboratively observing condition (2.17), which in turn was much better than their observing alone condition (0.97). In short, the ordering of their effect sizes for those three conditions in fact matches the pattern of our effect sizes completely.

4. Three tutoring hypotheses and analyses of the tutoring protocols

In this second half of this article, the three tutoring hypotheses proposed in Chi et al. (2001), differentiated globally in terms of whether the tutor, the tutee, or their interaction, is responsible for the benefits of learning from tutoring, will be further elaborated and evaluated. In order to differentiate among the three tutoring hypotheses, an added twist in the interpretation of our data is to look at how the tutoring dialogues affect the learning of the Collaborative Observers. Thus, this section of the paper reports analyses of the tutor-tutee dialogues from the benchmark Tutoring condition in order to further understand how the Tutees and the Collaborative Observers learn. This entire section therefore concerns the Tutees and the Collaborative Observers only.

4.1. Three hypothesis about tutoring effectiveness

Three general hypotheses have been proposed for the learning benefit from being tutored (Chi et al., 2001). This section elaborates these three hypotheses and briefly reviews prior evidence relevant to them. The first hypothesis, referred to as the tutor-centered pedagogical hypothesis (or in brief, *the tutor-centered hypothesis*), assumes that learning from tutoring is enhanced because the tutor undertakes pedagogical moves (such as explaining, scaffolding, giving feedback, or motivating) that are tailored to the tutees. This hypothesis similarly underlies research that examines effective and ineffective teaching practices (Shulman, 1986), in that it assumes the effectiveness of teaching affects student learning. Such an assumption may implicitly underlie tutoring research that searched for tutors' optimum pedagogical strategies and moves (Evens, Spitkovsky, Boyle, Michael, & Rovick, 1993; Hume, Michael, Rovick, & Evens, 1993; Lepper, Woolverton, Mumme, & Gurtner, 1991; Merrill, Reiser,

Merrill, & Landes, 1995; Merrill, Reiser, Ranney, & Trafton, 1992; Putnam, 1987; Sleeman, Kelly, Martinak, Ward, & Morre, 1989; VanLehn et al., 2003).

Crediting a tutor almost entirely for a tutee's learning is rational but actually without basis in evidence. Perhaps the hypothesis arose from three observations: (a) that powerful techniques are used by a few unique and exceptional orators and tutors such as Socrates (Collins, Brown, & Newman, 1989; Collins & Stevens, 1982); (b) that a tutor is generally knowledgeable about the content domain that she is tutoring; therefore, this domain expertise is confounded with the assumption that the tutor must also be an expert on the pedagogy of tutoring; and (c) that a tutor does typically control, lead, and dominate the tutorial conversation (Chi et al., 2001; Graesser, Person, & Magliano, 1995). Granted, one can determine that some tutorial moves might affect learning (specifically, feedback can accelerate learning in the context of problem-solving; Anderson, Corbett, Koedinger, & Pelletier, 1995). However, these three observations may be epiphenomena, in that the differential tutoring moves may not in fact be responsible for tutee's learning.

We can evaluate this tutor-centered pedagogical hypothesis in terms of three components: frequency, quality, and adaptiveness. That is, for the first component, if we assume that a tutor's move is responsible for a tutee's learning, then the more often such a pedagogical move is undertaken, the better the tutees ought to learn. Our prior results found no support for this frequency component in terms of correlations. For instance, we found that although our novice tutors explained frequently to tutees, the tutees did not seem to learn much from these explanations (Chi et al., 2001, Study 1).

The quality component was not examined directly in our prior study. One could argue that expert tutors might give excellent explanations that novice tutors could not, assuming that good instructional explanations facilitate learning much more so than poor instructional explanations (Eisenhart et al., 1993). Since the tutoring dialogues in this study involve an experienced teacher/tutor, we can infer the quality component by analyzing the frequency component again. If the same results are obtained here with this more expert-like Tutor as our prior results with novice tutors, then the evidence here would indirectly refute the quality component.

The third component of the tutor-centered hypothesis is adaptiveness. Adaptiveness is a very complex concept. It can refer to a tutor's selection of the appropriate moves, delivered at the right moment and based on a tutee's need for feedback and help (Murray & VanLehn, 2005). Thus, being adaptive can be operationalized to mean that (a) a tutor must choose the appropriate moves (or problems to be solved by the tutee) that are tailored to the tutee; (b) a tutor knows when to deliver his feedback, explanations, and scaffolding hints (such as contingent upon the correctness of a tutee's response; Wood, Wood, & Middleton, 1978); and (c) this knowledge must be gleaned from his continuous assessment of the tutee's competence and understanding. Moreover, assessment can mean from either a normative perspective or from the tutee's (or student's) perspective. For example, we found that inexperienced tutors could not assess tutees' deep understanding accurately from the students' perspective (Chi, Siler, & Jeong, 2004), whereas tutors are usually quite capable of assessing tutees' competence from the normative perspective (Putnam, 1987). In short, there is a scant set of evidence to test the many aspects of the adaptiveness component of the tutor-centered hypothesis. We will add a small piece of evidence to this scant set here.

The second hypothesis for the benefit of tutoring is the idea that a tutoring context, by definition, is one in which a tutee has greater opportunities to have a one-on-one dialogue with the tutor, as compared to a standard classroom context. This opportunity to be constructive potentially could cause the tutees to learn more. We called this the student-centered constructive hypothesis (or *the student-centered hypothesis*) to contrast the role of the tutees from the role of the tutor. We provided preliminary evidence in support of this hypothesis. For example, when the tutors were suppressed from giving any explanations and feedback at all, and could only give prompts (Study 2, Chi et al., 2001), the tutees learned just as effectively as when the tutors gave a substantial amount of explanations and feedback (Study 1, Chi et al., 2001). We attributed the tutees' learning to the constructive responses that they gave to tutors' scaffoldings.

Finally, the third proposed hypothesis is the interactive coordination hypothesis (or *the interaction hypothesis*), which states that tutoring effectiveness depends upon the joint or coordinated effort of both the tutor and the tutee. For example, our evidence showed that some tutor moves (such as scaffolding) were more beneficial for tutees' learning than other tutor moves (such as giving explanations; Chi et al., 2001, pp. 499–500). Moreover, when we encouraged the tutors to do more scaffolding than explaining, this resulted in an increase in the number of multi-turn deep tutor-tutee interactions (see fig. 9, Chi et al., 2001). Both of these results suggest that scaffolding can elicit more meaningful and elaborate joint construction. Although we could infer that these two results confirmed that some kind of interactions between a tutor and a tutee contributed more toward learning than other kinds, it was actually impossible to isolate the contributions of the tutees independently of the contributions of the tutors. That is, we could not discriminate whether the learning arose from the tutors' scaffoldings per se or from the tutees' constructive responses per se or from their interactions.

In sum, our previous studies (Chi et al., 2001; Chi et al., 2004) provided sufficient evidence to question the tutor-centered hypothesis and to highlight both the student-centered and the interaction hypotheses as potential accounts for tutees' learning. The current study hopes to provide additional evidence to support and/or refute these hypotheses, using a procedural domain (problem-solving) rather than a conceptual domain (human circulatory system), a single more expert-like tutor rather than multiple novice tutors, and college students rather than middle-school students as tutees. Moreover, by inferring the effectiveness of tutoring from the additional perspective of how the Collaborative Observers learn, we might gain better insight into all three hypotheses since the tutoring was not tailored to the Observers, nor were the Observers constructing responses to the Tutor, and moreover, the Observers heard not only what the Tutor said, but they also heard what the Tutees said.

4.2. Segmentation and grain size

Learning studies using complex materials, such as solving physics problems, can generate a massive amount of protocol data. Because of the labor-intensiveness of transcribing and coding such a massive amount of data, we tested a short-cut method and undertook duplicate coding for 20% of the data for the purpose of calculating interrater reliability. However, we did inject several "validating" analyses to gain further confidence in our coding. By this, we mean alternative codings, often at a different grain size, or with a different set of goals, to

see whether the results from different codings replicate each other or whether some codings replicate robust evidence in the literature.

We begin by explaining how the 10 tutoring videotapes were segmented in a short-cut way after they were transcribed. Each transcript was first segmented according to speaker turns. A turn, by definition, is speech by a single speaker (Traum & Heeman, 1997). Then the transcript was further segmented according to either the speaker's intonation (e.g., a falling tone, a rising tone), pauses, or changes in action (e.g., from talking to writing on the board or from reading the problem statement to writing on the board). Two coders independently segmented 20% (2 of the 10) tutoring video transcripts while watching the tutoring videos and agreed on 2466 (97.03% of the total) segments.

This short-cut method of segmentation, based on the structure of speech (turns, intonation, pauses, and changes in action) can be carried out much more objectively and rapidly than segmentation based on an analysis of the content of speech, as we have routinely done in the past (Chi, 1997; Chi et al., 2001). Therefore, it is important to know whether segmentation based on the structure of speech is adequate in comparison to segmentation based on the content, since the former can be more easily automated. To verify this, we selected the middle 20% of each of the 10 tutoring transcripts and coded according to the content method of segmentation (Chi, 1997). The segment boundaries were then compared across the two methods, yielding concordance rate of 89.1% for the 2,416 coding decisions made across the two systems. Not only does this result indicate a high level of agreement between the two methods, but the percentage of disagreements between the two methods was quite symmetric (5.4% of the time a segment was indicated by the content coding but not according to the structure coding; and 6.1% for the alternate instance), indicating that there was no systematic bias one way or the other in terms of segmenting at a consistent grain size.

Using the structure rather than the content of speech, a segment does nevertheless roughly correspond to what we have previously referred to as a *statement*; that is, to a single idea, presented by a single speaker within a turn. Thus, a segment is our smallest unit of analyses. The utterances made by the Tutor, shown below, were coded as three segments; the boundaries are shown by the double lines.

So you have therefore written the equation of motion.//

And from using the equation of motion you have been able to find out what would be the normal reaction for block A.//

Now similarly there is a equation of motion for block B.//

Segments can also be combined into interactive dialogue units when tutor-tutee responses are considered jointly, often in adjacent pairs of turns. Because a turn can contain multiple segments, the last segment within a turn (from the Tutor, for example) can be analyzed with the response in the next turn (by the Tutee), to create a dialogue unit. Finally, segments can also be combined into an episode unit. An episode corresponded to the consecutive talk and problem-solving segments that referred to the same problem-solving node, from the model of problem solutions (see Fig. 1 for an example of a problem solution model).

The results will be reported below in three sections, corresponding to the three grain sizes: segments within one turn, dialogues that are consecutive segments involving two turns, and

episodes often involving multiple turns. The details of the codings for each grain size will be unpacked as each result is being described.

4.2.1. Independent segment analyses

The Tutor, on average, made a total of 686 segments, whereas the Tutees averaged 443 segments per tutoring session. This approximate 3:2 tutor-tutee ratio is typical in tutoring, in which the tutor usually dominates the conversation by talking more (Chi et al., 2001; Graesser & Person, 1994). In our prior study, the tutor-tutee ratio was even more pronounced (621 tutor statements vs. 206 tutee statements, roughly a 3:1 ratio). The smaller difference in this current study may be attributed to the experience of this Tutor in the context of our research, in that he recognized the advantage of making fewer statements himself and eliciting more responses from the Tutees. One could perhaps take the ratio of tutor-tutee contributions as an index of tutor expertise, suggesting that our Tutor in fact is more of an expert tutor.

Overall, the tutorial dialogue, considering both the Tutor and the Tutees' moves, was far more extensive with the Poor Tutees (1393 mean number of tutor-tutee segments) than with the Good Tutees (864 segments). An obvious interpretation of this result is that the Poor Tutees needed more help. This overall greater amount of dialogue with the Poor Tutees translated into a greater frequency of all types of tutor moves; therefore, it is sometimes more appropriate to calculate the proportion and other times to use the frequency of moves in the analyses to be reported below.

4.2.1.1. Learning from the tutor's moves?: Tutor moves were defined as instructional segments, uttered by the Tutor, that were relevant to the pedagogical task of tutoring. Tutor segments were categorized as either an explaining move, a scaffolding move, a feedback move, or various other miscellaneous moves (such as summarizing, comprehension checking, tutor responding to tutee questions, false starts, and so forth). Tutor moves for the middle 20% of each of the 10 tutoring protocols were independently coded by two raters into these four categories. Based on the Kappa coefficient, the interrater reliability for this coding indicated substantial agreement ($\kappa = 0.758$). Subsequent analyses will focus on the three largest categories: explanations, scaffolding, and feedback segments only.

An explanation is an utterance in which the Tutor defines physics concepts or principles, provides an interpretation of important problem situation features, or describes how to carry out a particular procedure, the conventions used to carry out a particular mathematical or physics problem-solving step, or the outcome of applying some procedure. Below is an example of a tutor explanation, generated in one turn, containing four segments:

If there is a net force F, then there will be an acceleration, a, on that object.//
 If there is no force, then there is no acceleration.//
 So this is the equation which tells you that whether an object—an object is accelerated or not.//
 And umm, therefore, it is called the equation of motion.//

A scaffolding is defined as either a prompt that is content free (superficially, it gives away no information) or some kind of support for helping or guiding the tutees toward understanding. The support can take the form of a hint, an assertion with an expectation to fill in a blank, a direct or indirect question, and so forth. In Chi et al. (2001), we identified 14 different forms

Table 3
Correlation of Tutor and Tutee moves with Tutees' and Collaborative Observers' deep learning

	Average No. of Segments per Session	Proportion (%)	Tutees' Learning (<i>n</i> = 10)	Observers' Learning (<i>n</i> = 20)
Tutor instructional moves				
Scaffolding	245	36	N.S.	N.S.
Explanation	157	23	N.S.	N.S.
Feedback	130	19	Trend $r = -.603, p = .065$	N.S.
Other	154	22		
Total	686	100		
Tutee learning moves				
Substantive	230	52	Trend $r = .605, p = .064$	N.S.
Nonsubstantive	213	48	$r = -.899, p = .000$	N.S.
Total	443	100		
Tutee substantive moves				
Relevant follow-ups	99	43	$r = .641, p = .047$	Trend $r = .398, p = .082$
Irrelevant responses	131	57	Trend $r = .620, p = .056$	N.S.
Total	230	100		

of scaffolding. Below are three examples of scaffolding taken from different contexts in the protocols, each of one segment length:

Weight is the...?//
Acceleration due to...?//
When a force acts on body, uh, how does the body react to it?//

A feedback segment can be either a short positive (e.g., "right") or negative (e.g., "no, no") response about the correctness or incorrectness of what the Tutees said or did, or it can be more extensive, in terms of correcting what the Tutees did incorrectly (e.g., "No, the Earth") or elaborating further on what the Tutees did or stated (e.g., "No, it should be accelerating towards A and B"). In the latter two cases, the Tutor's feedback would be coded only as a corrective/elaborative feedback (and not double-coded as both a negative and a corrective/elaborative feedback). These feedback segments can be given to either correct or incorrect Tutee responses.

The top section of Table 3 shows the average number of segments per session and their proportion for each type of Tutor's instructional move. Note that scaffolding is the largest category of the Tutor's instructional moves, consisting of 36% of his total statements. In contrast, in our prior study, scaffolding consisted of only 5% of the total number of instructional moves. Likewise, explanations consisted of 23% of the total instructional moves, whereas in our prior study, the tutors' explanations consisted of 53% of the total statements (Chi et al., 2001, Fig. 2). The reversal in the ratio of explanations-to-scaffolding might be caused by the expertise of the current Tutor, whereas our prior study involved 11 novice tutors. In fact, one might consider the ratio of explanations to scaffolding moves as another index of our Tutor's pedagogical expertise.

Did the frequency of Tutor moves correlate with Tutees' learning? No. There were no significant correlations between the average number of Tutor's explanation nor scaffolding segments per se with either the Tutees' or the Collaborative Observers' matched deep step gains (see the last 2 columns of Table 3, top). This result replicates what was found in Chi et al. (2001). There, neither the tutors' explanations (Table 3) nor scaffoldings (Table 3, Model 2), correlated with deep learning. That is, if we extract from the protocols only the Tutor's moves in terms of the frequency of explanations and scaffoldings that the Tutor provided, then receiving and hearing those moves as independent monologues did not have an impact on either the Tutees' or the Observers' learning.

What about the Tutor's feedback? As shown in Table 3, there was a negative correlation between all types (positive, negative, corrective, elaborative) of Tutor feedback and the Tutees' learning ($r = -.603$) but no correlation with the Observers' learning, and the negative correlation with the Tutees' learning was marginally significant ($p = .065$). This marginal negative correlation between the Tutor's feedback and the Tutees' learning cannot be mediated by Tutees' errors because there is not a significant correlation between Tutees' errors and Tutees learning. That is, it is not the case that the more errors a tutee makes (thereby eliciting more tutor feedback), the less he is likely to learn, thus accounting for the negative correlation. This puzzling negative correlation will be examined more closely later.

4.2.1.2. Learning from the tutees' moves?: The preceding section analyzed the Tutor's moves independently of the Tutees' responses. Such an analysis, in essence, treated the Tutor's moves as instructional monologues, and there were no significant correlations between the frequency of the Tutor's moves with the Tutees' or the Observers' learning (except for a marginal negative correlation with feedback for the Tutees only). If neither the Tutees nor the Observers learned by considering the Tutor's independent moves, then how did they learn? In this section, we analyze the Tutees' independent learning moves.

Tutees' segments were categorized as either a substantive or a nonsubstantive learning move in terms of the content, regardless of the form of the segment, such as an assertion or a question. A substantive segment is defined as a meaningful contribution to an ongoing activity, such as problem solving, or a relevant response to the Tutor's explanations. For example, to the Tutor explanation shown below the Tutee's response would be coded as a substantive one:

Tutor: See this equation is true for constant acceleration.//
 Now the acceleration is constant here.//
 Forces are not changing on the weight so the acceleration is constant.//
 Tutee: The initial velocity is zero then.//

A nonsubstantive segment is defined as a continuer, a repetition, an agreement, or off-task remarks. To the Tutor's explanation shown above, if the Tutee had responded with "alright," then that would be coded as a nonsubstantive response.

The middle section of Table 3 showed that 52% of the Tutees' segments were substantive. The correlation of substantive moves with matched deep step gain was $r = .605$ and it approached significance ($p = .064$), whereas the correlation of nonsubstantive moves with matched deep step gain was strongly negative ($r = -.899$, $p = .000$). Thus, the Tutees learned only when they responded with substantive contributions, but they definitely did not learn

when they constructed nonsubstantive responses, again, replicating our previous results (Chi et al., 2001). Thus, being responsive per se is not sufficient; one must construct substantive responses in order to learn.

Substantive segments can be further divided into those that are relevant or irrelevant. Relevant substantive segments are those that are responsive to the Tutor's comments in the sense of building on or following up to the Tutor's comments. The following underlined segment would be an example of a relevant substantive response:

Tutor: If I push it, it's, velocity becomes some—something.//

Tutee: Mm hmm. [tutee nods yes]//

Tutor: So from zero to something, there is a change.//

Tutee: Ok, so yeah.// It wouldn't be a constant.//

Irrelevant responses are those that are not responsive to the Tutor's comments but are nonetheless substantive. The underlined example below is an example of an irrelevant but substantive response:

Tutor: It seems reasonable?//

Tutee: That the Earth is accelerating.//

Tutor: Because of these masses.//

Tutee: [tutee laughs] No. Those are some pretty big masses.//

Tutees benefited from constructing substantive responses, both relevant (the correlation is $r = .641$, $p = .047$) as well as irrelevant ones ($r = .620$, $p = .056$. See Table 3, bottom.) The Observers, however, seemed to be able to benefit somewhat only from overhearing the relevant responses (trend, $r = .398$, $p = .082$).

The fact that the Tutees could benefit from making substantive responses whether or not they were relevant replicates our overall self-explanation effect (Chi et al., 1994; McNamara, 2004) if we assume that irrelevant substantive responses are analogous to idiosyncratic self-explanations. In particular, in Chi et al. (1994), we claimed that students could learn whether they generated correct or incorrect self-explanations. A simple interpretation for this latter finding is that, although the substantive responses may seem irrelevant from the normative perspective, they can be conceived of as self-explanations that serve the Tutees' own purposes of repairing and refining their own understanding (Chi, 2000). This same interpretation can be used to explain the modest benefit Observers had from overhearing the relevant substantive follow-ups but not from overhearing the irrelevant responses, because the irrelevant ones would not make sense to an observer, since they served the Tutees' own purpose of repairing and refining their own understanding.

This result, that Tutees learned from constructing substantive responses, further reinforces our previous interpretation of Study 2 in Chi et al. (2001). There, the tutees seemed to have learned in an artificial tutoring condition in which the tutors were suppressed from explaining but encouraged to scaffold. The tutees in the suppressed condition learned just as well without tutors' explanations but with many more tutor scaffoldings (see Fig. 8, Chi et al., 2001). We had inferred then that the tutees must have learned from the benefit of constructing responses to the tutors' scaffoldings, and the result provided here further confirms that interpretation,

along with some evidence in VanLehn et al. (2003, tables 11 and 12), Litman and Forbes-Riley (2006), and Jackson, Person, and Graesser (2004).

4.2.1.3. Summary of segment-level analysis: Overall, the pattern of correlation results shows that the frequency of the Tutor's moves had mostly no effect on the Tutees' (nor the Observers') learning, replicating our tentative results from the 2001 study. Moreover, the Tutor's feedback moves were somewhat detrimental to the Tutees' learning. Thus, these results do not support the frequency component of the tutor-centered hypothesis. Moreover, because our Tutor is an experienced teacher, the lack of correlation between his instructional moves and Tutees' learning suggests indirectly that the quality component of the tutor-centered hypothesis is not supported either. Thus, there was no support for two of the three components of the tutor-centered hypothesis.

The Tutees' moves, however, did affect their own learning, but only if they constructed substantive responses (whether relevant or irrelevant). This finding, that the students' own construction is responsible for learning from tutoring, further supports the student-centered constructive hypothesis.

The Observers could not learn by overhearing either the Tutor's or the Tutees' independent moves, even if they were substantive. But there was a trend for a correlation with their learning when the Tutees' responses were not only substantive but relevant as well, most likely because substantive relevant responses are normative, whereas substantive irrelevant responses are specific to the Tutees' own mental models only. This trend will be examined in greater detail in the next section.

4.2.2. Interactive dialogue analyses

Testing the tutor-centered and the student-centered hypotheses involved analyzing Tutor's instructional moves and Tutees' learning moves independently. Even so, we often could not disambiguate whether the Tutees' learning arose from their own constructions or from receiving the Tutor's instructional moves. For example, as shown in the bottom of Table 3, the Tutees learned from constructing both relevant and irrelevant substantive responses. But we could not determine whether their learning arose from their own self-directed construction only, from receiving the Tutor's instructional moves, or from some interaction of the two. However, analyzing interactive dialogue units as well as analyzing from the perspective of the Observers' learning might allow us to differentiate the contributions of the Tutor, the Tutees, or their interactions toward the Tutees' learning. Accordingly, in this section, analyses of the tutoring protocols will take on a larger grain size, in terms of tutor-tutee dialogue units.

4.2.2.1. Tutees' relevant substantive follow-up responses to tutor's scaffolding and explanations: Since the Observers did not learn at all from overhearing the Tutees' irrelevant responses (Table 3, bottom), we focus only on the Tutees' relevant follow-up responses. Coding of relevant Tutee responses was actually interactive coding that examined adjacent pairs of turns, because relevance must be defined in the context of the content of the prior utterance. These prior Tutor utterances were either explanations or scaffoldings. There were no instances of Tutees making immediate relevant substantive responses to Tutor feedbacks because Tutor

feedbacks were immediately followed by either some other type of Tutor move before a Tutee had a chance to respond (e.g., feedback followed by a scaffolding or explanation), by a nonsubstantive Tutee move (e.g., a continuer or repetition of what the Tutor said without adding any new information), or by a Tutee nonsubstantive response (e.g., a request directed to the Tutor or an assertion like “I can do this math” or “Ok I see where you are going.”) Accordingly, we examined tutor-tutee dialogue units that were relevant Tutee responses that either followed a Tutor scaffolding or a Tutor explanation.

As shown at the bottom of Table 3, there were on average a total of 230 substantive segments made by each Tutee per tutoring session. Of these, only 99 of them were relevant follow-up responses to the Tutor’s scaffolding or explaining moves. Here is an example of a Tutee’s relevant follow-up (underlined) given to the Tutor’s scaffolding (more Tutor segments are provided for context) :

Tutor: No M is acceleration of what?//
 This force is acting on what?//
 Tutee: This force is acting on—the ground.//

And here is an example of a Tutee’s relevant follow-up given to the Tutor’s explanation:

Tutor: So this will be pulling this object to it.//
 So since A and the force that A and B are experiencing due to G is attractive force—force—directed toward G—//
 so G should be experiencing a force which is directed toward A and B//
 so that will be upward force//
 Tutee: Oh okay—so I have this backwards.//

For the Tutees, their learning correlated significantly with constructing a relevant follow-up to the Tutor’s scaffolding ($r = .656, p = .039$), more so than constructing a relevant follow-up to a Tutor’s explanations ($r = .576, p = .082$), although there is a trend here too (see Table 4). However, we cannot tease apart whether the Tutees learned as a result of receiving the Tutor’s scaffolding and explaining pedagogical moves, or from their own construction. Since the Observers were not constructing the responses, whether or not they learned by

Table 4

Correlation of the number of Tutor-Tutee relevant substantive interactive dialogue with Tutees’ and Observers’ deep learning

	Average No. per Session	Proportion (%)	Tutees’ Learning ($n = 10$)	Observers’ Learning ($n = 20$)
Tutor scaffolding followed by Tutees’ relevant substantive responses	59	60	$r = .656, p = .039$	$r = .434, p = .056$
Tutor explaining followed by Tutees’ relevant substantive responses	40	40	Trend $r = .576, p = .082$	N.S.
Total	99	100		

overhearing these tutor-tutee dialogue units would help differentiate the interpretations above. Table 4 (last column) shows that the Collaborative Observers learned significantly only when they overheard scaffolding-relevant follow-up dialogue units ($r = .434$, $p = .056$) but not explanation-relevant follow-up dialogue units. Their differentiated learning outcomes suggest that the source of the Tutees' learning might be different for the two types of instructional moves. We offer the interpretation that the Tutees learned from co-construction when the Tutor scaffolded them, and they learned from their own self-construction when the Tutor explained to them. That is, when the Tutor explained, the Tutees might have learned from constructing their own relevant substantive responses (and not from receiving the explanations since there was no correlation between Tutor's explanations and Tutee learning; see Table 3 again), whereas when the Tutor scaffolded, the Tutees might have learned from joint or co-constructing with the Tutor, in the general sense of building on to and/or extending upon (Tao & Gunstone, 1999) what the Tutor said.

Why would Tutor's scaffolding enhance joint construction more so than explaining? Note that a scaffolding tends to be a question, a prompt, or a hint, some move that is brief and expects a follow-up response, whereas an explanation tends to be longer and more didactic-like assertions that do not necessarily expect a response (see the two previous protocol examples). Therefore, by its very nature of being short and anticipatory, it is easier to understand and to build on a scaffolding move than an explaining move. In short, one interpretation is that the short and anticipatory nature of scaffolding invites joint construction.

One way to test our interpretation that scaffolding-relevant follow-up dialogue units are jointly constructed more so than explanation-relevant follow-ups is to analyze their coherence. Since joint construction involves building on and extending each other's utterances, one would expect jointly constructed dialogues to be more coherent than non-jointly constructed dialogues. To test this coherence hypothesis, we compared the cohesiveness of scaffolding-relevant follow-up and explanation-relevant follow-up dialogue units by using a computer tool called Coh-Matrix, which was developed for analyzing the cohesion, language characteristics, and readability of texts (McNamara, Louwerse, Cai, & Graesser, 2005). Applying this text analysis tool revealed that local cohesion based on adjacent sentences for scaffolding-relevant follow-up dialogue units ($M = \text{LSA local measure of cohesion of } 0.28$) was on average significantly more cohesive than explanation-relevant follow-up dialogue units ($M = \text{LSA local measure of cohesion of } 0.19$; $F[1,9] = 5.685$, $p = .041$; $d = 1.078$). In addition, there was a strong trend for global cohesion across sentences to be higher for scaffolding-relevant follow-up dialogue units ($M = \text{LSA global measure of cohesion of } 0.26$) than explanation-relevant follow-up dialogues ($M = \text{LSA global measure of cohesion of } 0.16$; $F[1,9] = 4.491$, $p = .063$; $d = 1.059$).

In short, the fact that scaffolding-relevant response units are more coherent than explanation-relevant response units supports our interpretation that scaffolding-relevant response units were more likely to be jointly constructed. Thus, the Tutees' learning when responding to the Tutor's scaffolding may arise from joint construction, supporting the interaction hypothesis, whereas the Tutees' learning when responding to the Tutor's explanation may arise from self-construction, supporting the student-centered hypothesis.

Why might overhearing scaffolding-relevant follow-up dialogues also be better for the Observers' learning than overhearing explanation-relevant follow-up dialogue units (see Table 4

again)? The same interpretation can be applied here as well: That is, scaffolding-relevant follow-up dialogues tend to be more easily understood by the Observers because they were shorter and more coherent than explanation-relevant follow-up dialogues. We tested whether scaffolding-relevant response units were in fact shorter than explanation-relevant response units by taking the middle 20% of each of the tutoring protocols and calculated the number of words produced. Scaffolding-relevant response dialogue units averaged 30 words, whereas explanation-relevant response dialogue units averaged 66 words. Our interpretation that shorter dialogue units are more comprehensible by an observer is compatible to some results of Van-Lehn et al. (2003); they also found that shorter learning opportunities were associated with more frequent gains.

4.2.2.2. Tutor's feedback to tutees' errors: We reported in Table 3 (in the Feedback row) that there was an overall negative correlation between the Tutor's feedback and the Tutees' learning. In order to understand this puzzling result, it may be more meaningful to examine the effect of feedback in an interactive way, such as examining only feedback that followed an error that a tutee made, presumably because it is more difficult to predict the utility of positive feedback, feedback usually given on a correct step. The frequency of positive feedback may also be a function of a tutor's style (such as giving more positive feedback for motivation purposes; Lepper et al., 1991). Moreover, Tutees may not learn as much by being told that their actions were correct. Thus, it seems more informative to analyze the effect of the Tutor's negative feedback to errors only.

Although a majority of the studies in the tutoring literature discuss feedback in terms of negative ones, the choice of giving a negative feedback is not at the discretion of the tutor, since it obviously depends on whether an error was made in the first place. However, the Tutor does have control over whether the negative feedback contains only the correct answer, or whether the negative feedback also includes elaborations and justifications. In short, feedback to errors can take one of three forms. Besides giving a negative feedback saying that the response is incorrect or "No," the Tutor has the additional option of giving a corrective feedback in which the Tutor basically gave the correct answer, such as:

Tutee: [Tutee writes * g] Times gravity.//
 Tutor: Times acceleration due to gravity.//
 Don't say gravity.//

On the other hand, a tutor can also give an elaborative feedback to an error, such as:

Tutee: FN would be//
 would FN be mass of A plus mass of B? Or?//
 Tutor: Again you—a force cannot be mass.//
 These are two distinct quantities.//

Examining these latter three forms of feedback (negative, corrective, and elaborative) corresponds to analyzing interactive dialogue units of an error followed by a feedback segment.

Table 5 (1st column) shows the average number of feedback-to-error dialogue units for the Good and the Poor Tutees. It is not surprising that there are almost twice as many feedback-to-error units for the Poor Tutees since they committed more errors during tutoring ($M = 89$)

Table 5

The average frequency per session, correlation, and distribution of Tutor feedback to Good and Poor Tutees' errors

Breakdown of Feedback to Errors						
	Average No. of Tutor Feedback to Errors	Correlation of Average No. of Feedback With Tutees' Learning ($n = 10$)	Correlation of Average No. of Feedback With Observers' Learning ($n = 20$)	Negative Feedback	Corrective Feedback	Elaborative Feedback
Good Tutees	43	N.S.	N.S.	15 (34%)	19 (43%)	10 (23%)
Poor Tutees	80	$r = -.882, p = .048$	$r = -.835, p = .003$	26 (32%)	41 (52%)	13 (16%)

than the Good Tutees, who committed fewer errors ($M = 56$), as mentioned earlier. Given that errors tend to elicit feedback, the contrast in the frequency of feedback to errors between the Good and the Poor Tutees makes sense.

The contrastive approach clarifies a possible reason for the puzzling overall marginal negative correlation between the Tutor's feedback and the Tutees' learning in Table 3. When the Tutor's feedback to errors were correlated separately for the Good and the Poor Tutees, the overall marginal, negative correlation became an even stronger, negative correlation for the Poor Tutees only ($r = -.882, p = .048$, see column 2, Table 5). This suggests that the detrimental effect of the Tutor's feedback only affected the Poor Tutees, whereas the Tutor's feedback to errors had no effect on the Good Tutees' learning.

A similar pattern of a strong negative correlation between the Tutor's feedback to errors and learning occurred for the Collaborative Observers as well ($r = -.835, p = .003$, see 3rd column in Table 5). That is, the Observers suffered when they observed the Poor Tapes, in terms of the frequency of feedback to errors.

The interpretation we offer is the following. Feedback to errors has no effect on the Good Tutees perhaps because they can learn even without feedback; that is, they can ignore the feedback. The Poor Tutees, on the other hand, could not benefit from the Tutor's feedback to their errors perhaps they could not make sense of the feedback, so that the more feedback they received to their errors, the more confused they were (thus less learning); and such confusion might have affected the learning of the Observers who watched their tapes. Recall that we reported earlier that the Poor Tutees overall did express confusion twice as frequently as the Good Tutees. Thus, the Poor Tutees had difficulty making sense of the Tutor's feedback.

But why might the Poor Tutees have difficulty making sense of the Tutor's feedback? One possible reason is that the feedback they received was less informative. For example, corrective feedback is less informative because it only gave the correct answer without further justifications, as in elaborative feedback. Table 5 (the last 3 columns) shows a distribution of the three different types of feedback (negative, corrective, elaborative) to errors. Although the distribution of the three types of feedback the Tutor gave is similar for the Good versus the Poor Tutees (both groups received the lowest proportion of elaborative feedback and highest proportion of corrective feedback), Poor Tutees received proportionately more corrective

feedback than elaborative feedback (52 vs. 16%), as compared to Good Tutees (43 vs. 23%). The contrast in the difference between the corrective and elaborative feedback for the Poor Tutees (36%) and the Good Tutees (20%) was significant ($F[1,8] = 5.188, p = .052$). In other words, the Poor Tutees received significantly more corrective feedback than elaborative feedback ($F[1,4] = 32.106, p = .005$), whereas there was no significant difference in the two types of feedback received by the Good Tutees. Because corrective feedback is less elaborative and contains no justifications, it may be more difficult for Poor Tutees to make sense of corrective feedback, which is the predominant kind of negative feedback that they received. Not making sense of the corrective feedback they received in turn affected how well the Observers could learn from overhearing them as well.

Thus, the earlier analyses of looking only at Tutor's feedback as independent moves, masked much stronger correlational effects when we analyzed feedback in an interactive and contrastive way. Basically, a tutor's feedback to errors seems harmless to Good Tutees and their Observers but detrimental to Poor Tutees and their Observers. This suggests that feedback per se is not the only critical factor, but what kind of feedback a tutor gives, and whether or not tutees can assimilate, understand, and use the feedback, thus supporting the interaction hypothesis. As reported earlier, the Poor Tutees expressed more confusion than the Good Tutees, perhaps because the feedback they received was less elaborative. Overhearing the Poor Tutees' feedback-to-error dialogue units must have had a detrimental effect on the Observers' learning as well.

4.2.2.3. Summary of dialogue-level analyses: The first set of analyses showed that the most effective form of dialogue units are scaffoldings followed by relevant substantive Tutee responses (see last 2 columns in Table 4), in terms of both the Tutees and the Observers' learning. We surmise that Tutees learned from them because they could jointly construct meaningful follow-up responses to the Tutor's scaffoldings, but less so to the Tutor's explanations. We assumed that jointly constructed dialogues may be shorter and more coherent, and scaffolding-relevant response dialogue units did turn out to be more coherent than explanation-response dialogue units, based on the Coh-Metrix analysis. The finding that the Observers also learned only when they overheard scaffolding-relevant response dialogue units is consistent with the coherence interpretation. Additionally, scaffolding response units may be more understandable than explanation response units because they tend to be shorter, as confirmed by the word count analysis. These findings provide evidence in support of the interaction hypothesis.

The second set of analyses examined feedback to errors. We found that feedback to errors was detrimental to Poor Tutees and Observers of their tapes but not to the Good Tutees and Observers of their tapes. The interpretation we offered was that Poor Tutees needed the feedback and yet possibly could not make sense of the feedback since the Tutor's feedback to them was more of the corrective kind rather than the elaborative kind. Corrective feedback basically gave only the right answer, whereas elaborative feedback gave the justification as well. In short, Tutees' learning is a function of both whether or not they can make sense of a tutor's feedback as well as whether a tutor gives them more elaborative feedback, again, supporting the interaction hypothesis. Thus, the differential learning gains of the Good versus the Poor Tutees as a function of feedback to errors further underscore the importance of the

Table 6
Frequency and correlations for all node episodes with Tutees' and Observers' deep learning

	Average Number Per Session	Tutees' Learning ($n = 10$)	Observers' Learning ($n = 20$)
Tutor	32	N.S.	N.S.
Tutor and Tutee	55	$r = 0.646, p = .043$	$r = 0.457, p = .043$
Tutees	16	$r = 0.637, p = .047$	Trend $r = 0.418, p = .067$

role of the tutees, in being able to make sense of the feedback, and not merely the role of a tutor, in terms of whether the right kind of feedback was given or not.

4.2.3. Episode analyses

In the prior dialogue analyses, we inferred that scaffolding-relevant follow-up units were jointly constructed because they were more coherent. However, we can directly code dialogue units as either jointly constructed or independently constructed by looking at a larger grain size. This would allow us to test the interaction hypothesis more directly. Accordingly, another pass at coding the protocols was undertaken at a larger episode-level grain size.

Segments in the tutoring protocols were combined into episodes. An episode is usually a multi-turn dialogue unit bounded by utterances whose content is relevant to a specific solution node (as shown in Fig. 1). Appendix B illustrates several episodes. For example, Episode III is relevant to Node 2.2.2 in Fig. 1. The appendix in its entirety can be found at <http://www.cogsci.rip.edu/CSJarchive/Supplemental/Index.html>.

4.2.3.1. Joint and independent coverage of all nodes: For each episode, we differentiated whether the substantive contributions were initiated and covered by the Tutor alone (as in Episode II), the Tutees alone (as in Episode III), or jointly by both the Tutor and the Tutees (as in Episodes IV, V, see Appendix B).

Table 6 shows that a majority of the episodes (55 per tutoring session) were jointly covered by the Tutor and the Tutee, followed by 32 episodes covered independently by the Tutor and 16 independently covered by the Tutees. If we assume that joint coverage involves more scaffolding and independent Tutor coverage involves more explaining, then this difference between the frequency of joint coverage and independent Tutor coverage mirrors the results of greater frequency of Tutor scaffolding than explaining (see Table 3 again).

If interacting with the Tutor facilitates learning, then there should be a significant correlation between the frequency of joint coverage and Tutees' learning. Table 6 shows that Tutees indeed learned when they jointly covered a node with the Tutor ($r = 0.646, p = .043$), thereby supporting the interacting hypothesis. Moreover, the Tutees also learned when they covered the nodes independently ($r = 0.637, p = .047$), suggesting that independent coverage obviously required them to be constructive, thereby leading to learning, thus supporting the student-centered hypothesis. The significant correlation of the Tutees' independent coverage of nodes replicates the significant correlation of Tutees' substantive moves at the segment level (Table 3). Thus, analyses at two different grain sizes produce the same pattern of results.

Finally, the Tutees did not learn when the Tutor independently covered a node (Table 6), just as they did not learn when the Tutor's scaffolding and explaining moves were considered independently (Table 3), thus weakening the importance of the tutor-centered hypothesis.

Can the Observers' learning further confirm the interacting and the student-centered hypotheses as well as any of our prior interpretations? The Observers likewise learned from overhearing joint coverage of nodes ($r = 0.457$, $p = .043$) but not from the Tutor's coverage of nodes. Again, if we assume that joint coverage involves more scaffolding and independent Tutor coverage involves more explaining, then the same interpretation offered for the results reported in Table 5 can be applied here as well; that is, Observers learn from overhearing joint coverage because joint coverage episodes are more coherent and short, containing scaffolding-response dialogues, whereas Tutor's independent coverage may be less coherent and long. The Collaborative Observers also benefited somewhat from overhearing Tutees' independent coverage of a node (a trend). Their weaker learning from overhearing the Tutees' independent coverage of a node (as compared to joint coverage) reinforces the interpretation that a Tutees' construction often serves their own purposes, and may be less comprehensible to others (Chi, 2000), consistent with the lack of correlation between the Observers' learning and Tutees' irrelevant substantive responses (see Table 3 again).

The contrast between the Observers' learning from overhearing the Tutees' independent coverage but not from overhearing the Tutor's independent coverage is related to some findings in the literature with respect to learning from an expert versus a peer. For example, Hinds, Patterson, and Pfeffer (2001) have found that learners performed better when instructed by novices than by experts in an electronic wiring task. Likewise, Cho, Schunn, and Charney (2006) found that students are far more able to incorporate feedback from their peers than from their instructor in a writing task. These findings, along with the result here of both the Tutees' and the Observers' failure to learn from the Tutor's independent coverage, are consistent with the finding that Tutees also do not learn from receiving the Tutor's explanations (as shown by a lack of correlation in Table 3).

4.2.3.2. Summary of episode analyses: In sum, analyses at the episode level provide further evidence to support both the student-centered and the interaction hypothesis but no evidence in support of the tutor-centered hypothesis. The correlation of learning with joint coverage of problem-solving nodes supported the interaction hypothesis, while the correlation of learning with the tutee's independent coverage of the nodes supported the student-centered hypothesis. The lack of any correlation of learning with Tutor's independent coverage further undermines the tutor-centered hypothesis.

4.3. Is the tutor adaptive?

We proposed above that the tutor-centered hypothesis can be evaluated in terms of the frequency and quality of a tutor's moves and a tutor's adaptiveness. Adaptiveness includes choice of moves, timing of moves, and assessment of tutees' understanding. Assessment furthermore can take one of two forms. Normative assessment means that a tutor evaluates whether a tutee is getting something right, as a function of the formal knowledge of a discipline. There is no question that tutors, knowledgeable about their domains, are competent

at doing this and base their feedback on normative knowledge (Putnam, 1987). However, assessment can also mean evaluating a tutee's understanding from the students' perspective, such as knowing what a tutee's misunderstanding is or in what ways is a tutee's mental model flawed. Our prior findings have shown that neither an expert tutor nor novice tutors were very accurate at assessing their tutees' understanding. In the domain of physics, we found an expert tutor to often overlook the tutee's misunderstanding (Chi, 1996). In the domain of the circulatory system, when we directly assessed tutors' conceptions of their tutees' mental model of the circulatory system while tutoring, we found their conceptions to be completely inaccurate (Chi et al., 2004). If a tutor cannot accurately assess a tutee's misunderstanding from a student's perspective, then he cannot be adaptive from this student-model perspective.

In addition, the main finding reported in this article, the fact that the Observers can learn as well as the Tutees, also suggests indirectly that adaptiveness cannot be a powerful feature of tutoring effectiveness, since the Tutor obviously could not be adapting to the specific needs of the Observers. A specific finding of this study also questions the adaptiveness of the Tutor. This is the result showing that the Tutor gave more corrective than elaborative feedback to the Poor Tutees (Table 5). One could argue that this is counterproductive and not adaptive in that the Poor Tutees needed more elaborative feedback. Aside from these negative findings, can we provide any positive evidence for a tutor's adaptiveness?

One manifestation of adaptiveness, as suggested above, is to know what kind of problems to present to the tutees. For example, one would expect that the Tutor would choose the more challenging problems for the Good Tutees. As noted in Appendix A, the Tutor designed the four tutoring problems and rank ordered their difficulty from easiest (Problem 1) to the hardest (Problem 4). Therefore, a simple but gross measure of his adaptiveness is to see whether or not he presented the more challenging problems to the Good Tutees. Although the hardest Problem 4 was presented only twice to the Good Tutees, to get more data points, we combined the two easier problems (1 and 2) and the two harder problems (3 and 4) to see which ones were assigned to be tutored. There was absolutely no difference between the Good and the Poor Tutees: On average, the Tutees in both groups were assigned the easier problems exactly seven times and the harder problems exactly three times. Thus, although this measure of adaptiveness (using only two sets of problems) is not very sensitive, the result at minimum suggests that we cannot conclude that the Tutor was adaptive in terms of his selection of which problems to use in tutoring as a way to tailor his instruction to the competence and needs of a tutee.

5. Conclusion

The two overarching goals of this research were to design an alternative learning environment that facilitates learning from tutoring and can be more easily adapted and scaled up for a variety of learning contexts, such as online as well as classroom learning, and to further our understanding of tutoring effectiveness. The alternative learning environment is observing tutoring collaboratively. The motivation for designing such an environment was to leverage and combine the benefits of tutoring, collaborating, and the potential benefit of observing.

Comparing five different contexts of learning (tutoring, observing collaboratively, collaborating, observing alone, and studying alone), we replicated the tutoring literature by showing that human tutoring is indeed the most effective form of instruction. More interestingly, students in the alternative learning environment of observing tutoring collaboratively seemed to learn as effectively as students participating in tutoring. In fact, when one observes tutoring of competent tutees (the Good Tutees), learning by the Observers is totally equivalent to (in fact slightly exceeded) learning by the Tutees who participated interactively in the tutoring. Such results suggest that it is interacting per se that may account for learning (such as interacting with a peer) and not necessarily interacting with a tutor. Even more impressive are the learning gains of Collaborative Observers who were poor learners when they watched good learners being tutored. Since learning from tutoring has historically manifested the highest amount of learning gains, to find another learning environment that can match and exceed this benchmark, in the case of the poor learners, is extremely promising.

The results from the target observing collaboratively condition provided one explanation for the discrepancy in the literature about the benefit of observational learning for complex cognitive tasks. The conjecture we proposed is that the discrepancy in the literature may have arisen from the variability from study-to-study in terms of how active and engaged the observer was. This active/constructive/interactive observing hypothesis was supported in four ways in this study. First, the mere fact that the Collaborative Observers could learn as well as the Tutees who participated in tutoring, suggests that this can be accounted for by the interactions of the Collaborative Observers per se, without interacting directly with a tutor. Second, the fact that the more interactive the Collaborative Observers were with each other while observing, the more they learned lends further support to the active/constructive/interactive observing hypothesis. Third, two conditions of observations were manipulated, observing collaboratively and observing alone. Collaborative Observers learned more than the Lone Observers, confirming our hypothesis that being more constructive, which was more likely in the collaborative condition, will enhance learning from observing. Finally, we teased apart the Lone Observers into those who were active versus those who were more passive. We found that the active Lone Observers learned more than the more passive Lone Observers, again confirming our hypothesis. In short, these four results seem to support unambiguously the conjecture that variability in engagement might have explained the discrepancy in the literature, especially given that the task predominantly used in the vicarious learning literature involved a single observer only.

The research findings shed further light on explaining why tutoring is effective. Consistent with our prior results (Chi et al., 2001), there is no question that Tutees learned when they made substantive contributions, regardless of the relevancy of their substantive contributions (see Table 3), as well as when they covered nodes themselves (Table 6), thus supporting the student-centered constructive hypothesis.

The Tutor can contribute toward Tutees' learning more by scaffolding the Tutees than by explaining to them (see Table 4), presumably because scaffolding enabled the Tutees to jointly construct coherent follow-up responses, thus supporting the interactive coordination hypothesis. The Tutees also learned when they covered a node jointly with the Tutor. Finally, the Tutor's feedback to errors was particularly harmful to the Poor Tutees and their Observers,

consistent with the interpretation that Poor Tutees found the feedback confusing, in part because the Tutor gave them more corrective than elaborative feedback. Thus, it is not the feedback per se that determined the Tutees' learning but whether the Tutees could make sense of the feedback and what kind of feedback the Tutor was more likely to give. In short, there is substantial evidence to support the interaction hypothesis, revealed largely from analyzing the protocol data at a both a two-turn dialogue unit and multi-turn episode unit of analyses.

Although tutoring effectiveness has traditionally been attributed to the skill of the tutor per se, we could find no evidence of learning from considering the tutor's contributions alone, using analyses at various grain sizes. Although some tutor moves were better than others (scaffolding is better than explaining; see Table 4), they were better because of the responses the Tutees could construct, not because they were good instructional moves themselves (see Table 3). Such results extend and support our previous findings and conjectures (Chi et al., 2001), wherein we could only show in an indirect way that tutors' explanations were not effective by suppressing tutors' explanations. However, given that those were novice tutors, one may be skeptical of the results of that prior study because those tutors' explanations may have been of lower quality (although such skepticism is not well-founded given the results of by Cho et al., 2006, and Hinds et al., 2001, showing that learners benefit more from novice instructors). The results of the current study, using a more expert-like tutor who presumably was capable of giving quality explanations, reconfirm the interpretation of the prior study. Overall, there was very little evidence to support the tutor-centered hypothesis in terms of frequency, quality, and adaptiveness (although we have scant evidence for the adaptiveness component of this hypothesis). In short, in a very different domain, with a different age group, these data once again undermine the influence of the tutor and further support the contributions of the tutees themselves, and their interactions with the tutor, as responsible for learning.

Although several of our analyses relied extensively on correlations, we believe that in the majority of the cases, we can infer causality since the intervention occurred prior to the learning outcome. Moreover, we relied on the patterns of correlations for our interpretations rather than on the values of individual correlations. Finally, despite a low sample size, the correlations were often quite substantial and learning was measured in terms of long-term (several days post-training) deep knowledge gains.

The finding that students can learn by observing tutoring vicariously has promising implications for how individual classroom interactions between a teacher and a student (such as at the blackboard) can be productive for the rest of the students in the class. Our finding basically supports Rogoff and colleagues' argument that learning through observation is a valuable but often overlooked practice in mainstream schooling (Rogoff, Paradise, Arauz, Correa-Chavez, & Angelillo, 2003). Such finding also has implication for how databases of reusable dialogues can be created as a resource for distance learners (Mayes, Dineen, McKendree, & Lee, 2001) and for online environments (Hudson & Bruckman, 2004). Finally, the findings that observers tend to learn in dialogues that involve the Tutees emphasize the importance of learning from peers, from both teaching a peer (Roscoe & Chi, 2007) as well as receiving comments and questions from a peer (Roscoe & Chi, in press).

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