

# Tradeoff between Problem-solving and Learning Goals: Two Experiments for Demonstrating Assistance Dilemma

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## Abstract

Recent intelligent tutoring systems give participants various types of supports. We hypothesize that a high level of support activates participants' orientation to problem-solving goals but reduces the priority of attaining learning goals; as a result, higher problem-solving performance is attained, but the learning effect is reduced. We tested this hypothesis by using two relatively largely different experimental tasks: Tower of Hanoi puzzle as a simple problem solving task and Natural Deduction learning as a more complex learning task. Overall results supported our hypothesis and were discussed from the viewpoint of the assistance dilemma.

**Keywords:** Problem solving goal; Learning goal; Assistance dilemma.

## Introduction

Recently, highly interactive intelligent tutoring systems have been developed whose design principles come from cognitive science theories. A series of cognitive tutors has been constructed based on the ACT-R theory (Anderson, Corbett, Koedinger, & Pelletier, 1995). Intelligent tutoring systems give participants various feedback such as verification, correct response, try again encouragement, error flagging, and elaboration messages (Shute, 2008). In the interaction design between a tutoring system and learners, feedback to learners is a central issue.

In this context, the assistance dilemma has been recognized. Koedinger and Alevan pointed out a crucial question (Koedinger & Alevan, 2007): How should learning environments balance assistance giving and withholding to achieve optimal learning? High assistance sometimes provides successful scaffolding and improves learning, but at other times it elicits superficial responses without consideration from students. On the other hand, low assistance sometimes encourages students to make a large effort, but other times results in enormous errors and interferes with effective learning.

We reformulate the assistance dilemma as a tradeoff of selecting either the problem-solving goal or the learning goal. In a representative situation, participants learn while solving instance problems given by a tutoring system. Attaining the problem-solving goal means solving such instance problems as accurately and rapidly as possible. However, the learning goal requires another attainment that is usually more essential. A primary objective is not to solve instance problems but to learn by solving instances. Dweck classified two types of goals: learning and performance (Dweck, 1986; Ames, 1992). Highly motivated children tend to set learning goals to

increase their competence to understand or master something new rather than just solving problems. Comparing the learning and problem-solving goals in our current study corresponds to Dweck's learning and performance goals. Achieving a problem-solving goal is measured by the solution time and the error ratio for solving problems in the learning phase. The learning goal is usually measured by a posttest after the learning phase.

Another important difference between the two goals is that the problem-solving goal can be achieved with the support of a tutoring system, but the learning goal should be reached without supports of a tutoring system. Achieving the learning goal is usually measured in a setting without tutoring system support because learners should solve problems by themselves without external support from a tutoring system. The need for support means that participants do not complete the learning.

Participant goal setting may be influenced by the feedback information from a tutoring system. One perspective for characterizing the feedback is directive and facilitative (Black & William, 1998). Directive feedback tells participants what needs to be fixed in the next step. Such feedback tends to be more specific than facilitative feedback, which provides participants with comments and suggestions directly relating to the problem-solving. When participants are solving a problem, directive feedback may guide them to focus on the problem-solving goal.

Another perspective for characterizing feedback is its timing. Researchers have addressed whether feedback should be delivered immediately or delayed. Delayed means that it occurs minutes, hours, or even weeks later. Mathan and Koedinger reviewed various studies and concluded that timing effects emerge interactively with other factors such as task difficulty and individual student needs or characteristics (Mathan & Koedinger, 2002). Immediate feedback may facilitate problem-solving goals because participants are repeatedly given indications for determining what to do next when solving a problem.

In the context of the investigation of the assistance dilemma issue, we control the levels of support (LOS) in the following experiments. A high level of support means that more direct and immediate feedback is given. Our hypothesis is that a high level of support activates participants' orientation to problem-solving goals and reduces the priority of attaining

learning goals. This hypothesis predicts that in the high level support condition, the problem-solving performance is higher than in the low level support condition, but the learning effect was reduced; therefore in the posttest where no supports are given, participants who learned in the high level support condition score lower than those in the low level support condition.

We tested this hypothesis using two experimental tasks. In Experiment 1 we used the Tower of Hanoi (TOH) puzzle, which is one representative experimental task widely used in problems-solving studies. In Experiment 2, the participants engaged in a natural deduction (ND) task.

TOH is a simpler task. The problem space is systematically organized and is not so large. Problem solving is achieved by only one operator that corresponds to disk movement. The knowledge and strategies for the solution are represented by less than ten production rules. ND is a more complex task. Its problem space is much larger than that of TOH. To solve problems, since participants must acquire many kinds of inference rules and solution strategies, a complete model for solving ND problems consists of around a hundred production rules. In addition, TOH is basically a problem-solving task, but ND is a learning task. The participants in Experiment 1 joined the experiment in a laboratory setting; those in Experiment 2 engaged in it in a learning context. We confirmed our hypothesis using two relatively largely different experimental tasks.

## Experiment 1

### Task

The six disks TOH puzzle was used as an experimental task.

### Experimental system

The participants individually engaged in the task using an experimental environment established on a personal computer. Figure 1 shows an example screenshot of the experimental system. The participants selected one of the possible disk movements by clicking a button with a mouse. A production system model was mounted on the system to solve TOH by the perceptual strategy. The model infers the next step, the next five steps, and the next nine steps for reaching the goal state through the minimum steps and presents the participants the best next state, the best state after five, and nine steps as a hint.

The LOS was manipulated by the presented hints. In the highest LOS condition, the participants were presented the next step at every problem-solving trial. In other conditions where the best step after five or nine steps was presented, the participants were given such hints at every five or nine problem-solving trials. Higher supports mean direct and immediate feedback; therefore, the participants in these two conditions were given lower levels of support than those in the next step condition. Additionally, in the lowest LOS condition, the participants were given no hint information.

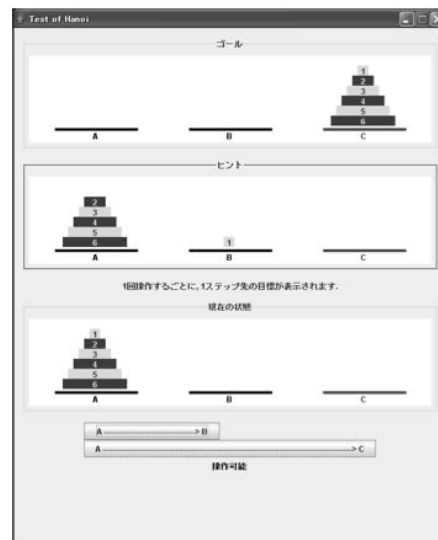


Figure 1: Example screen shot of experimental system for TOH. The upper and lower windows show the goal state and the current state. The middle window presents hint information; in this case the next one step is presented.

### Participants and Procedure

Seventy-one participants joined our experiment. 17, 19, 17, and 18 participants were assigned to the one step, five steps, nine steps, and no hints conditions, respectively. The experiment lasted 90 minutes. The participants were instructed to learn strategies for solving TOH and informed that after the learning session, a posttest would be performed to test their degree of skill acquisition.

In the initial stage of the experiment, the participants learned the constraints of the disk movements and how to use the experimental system. In the learning phase, they solved various types of six-disk-TOH problems in 40 minutes in one of the four experimental conditions. When one problem was completed, the next was given. After the learning phase, a posttest was performed in which the participants solved a test problem by themselves without hint information.

### Result

As a problem-solving performance measure, we used normalized steps for the solution in the learning phase. Figure 2<sup>1</sup> shows the average steps for the solution where the index indicated in the vertical axis was normalized by dividing the solution steps that the participants actually needed to follow by the minimum steps for reaching the goal state from the initial state in each problem. The value, 1.0, means the completed solution, and larger values indicate a poorer solution. The normalized steps needed for the solution were fewer in the one step, five, and nine step conditions where

<sup>1</sup>Note that in figures 2, 4, and 6, the value of the vertical axis is reversed to compare those with Figure 9 in conclusion.

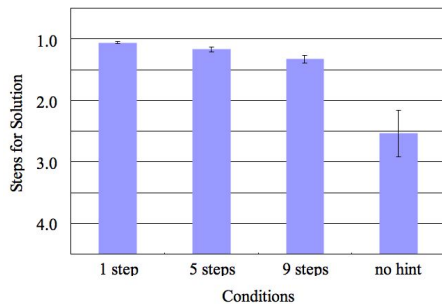


Figure 2: Average steps for solving problems in learning phase (TOH). The value of the vertical axis is reversed to represent higher values as high problem-solving performances, i.e., value 1.0 means the optimal problem solving. An ANOVA indicates that the main effect of Conditions factor was significant ( $F(3, 67) = 12.5, p < 0.01$ ). Fisher's LSD analysis shows significant differences between one step and no hints ( $p < 0.01$ ), five steps and no hints ( $p < 0.01$ ), and nine steps and no hints ( $p < 0.01$ ).

hint information was presented than those in the no hint condition. Our prediction was confirmed because the result of the problem-solving performance was worst in the lowest LOS condition. However, we did not detect statistically significant differences among the three hint conditions. The normalized steps in the three conditions almost reached 1.0. This means that the hint information was sufficient for reducing the trial and error behavior of the participants, even in the nine step condition.

Next, to investigate to what degree each participant thoroughly considered rational actions in each problem-solving step, we calculated the average time to decide each disk movement. We assumed that the priority of the problem-solving goal over the learning goal reduces this consideration time. Figure 3 shows the time that passed between one disk movement and the next. The time in the one step condition was shorter than in the five and nine step conditions, confirming our prediction. However, in the no hit condition, the time was also shorter than the five and nine step conditions, contradicting our prediction.

Next, as a learning performance measure, we used the normalized steps for the solution in the posttest. Figure 4 shows the result. The average steps in the nine steps condition were fewer than those in the one step and no hint conditions. The graph shows that in the three conditions (one, five, and nine step conditions) where hint information was presented, as lower LOSs were given, the learning effect increased, confirming our prediction. However, in the no hint condition, the performance was poorer than that in the higher LOS (nine steps) condition, contradicting our prediction.

Contradictory to our prediction, in the no hint condition, the time for deciding the next disk movement was shorter, and the learning effect was poorer. Perhaps in the learning phase,

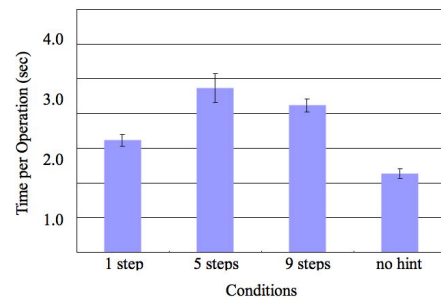


Figure 3: Average time for deciding disk movement (TOH). An ANOVA indicates that the main effect of Conditions factor was significant ( $F(3, 67) = 18.0, p < 0.01$ ). Fisher's LSD analysis shows significant differences between one and five steps ( $p < 0.01$ ), one and nine steps ( $p < 0.01$ ), five steps and no hints ( $p < 0.01$ ), and nine steps and no hints ( $p < 0.01$ ).

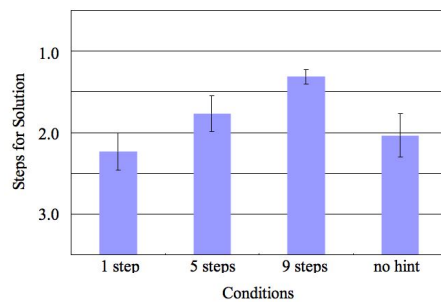


Figure 4: Average steps for solving problems in posttest (TOH). The value of the vertical axis is reversed to represent higher values as high problem-solving performances, i.e., value 1.0 means the optimal problem solving. An ANOVA indicates that the main effect of Conditions was significant ( $F(3, 67) = 3.25, p < 0.05$ ). Fisher's LSD analysis shows significant differences between one and nine steps ( $p < 0.01$ ) and nine steps and no hints ( $p < 0.05$ ).

it was difficult for the participants to learn strategies without hint presentation. This point will be mentioned below in the discussion and conclusion.

## Experiment 2

### Task

Natural deduction (ND) is a kind of proof calculus: e. g., inducing a proposition  $\neg Q \rightarrow \neg P$  from a premise  $P \rightarrow Q$ . Logical reasoning is expressed by inference rules closely related to a natural way of reasoning. They learned nine basic rules and five formal strategies, all of which are fundamental knowledge in ND. Most problems can be solved using this knowledge.

### Experimental system

The experimental system used in Experiment 2 was developed as a tutoring system for teaching ND to university un-

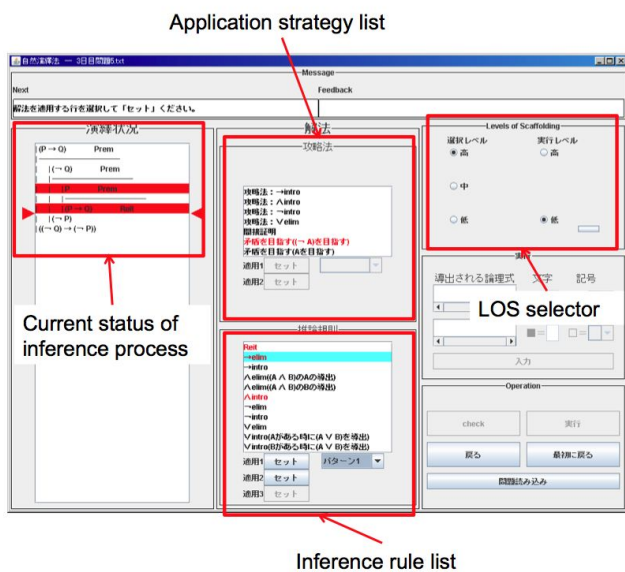


Figure 5: Example screen shot of ND tutoring system. The left side window shows a current status of inference processes where the red items are propositions to which the selected inference rule should be applied. The upper and lower center windows show a strategy list and an inference rule list where the red items are applicable candidates. The right upper window shows the LOS selector where the levels of support are controlled. In the current experiment, LOS was fixed based on the experimental manipulation.

dergraduates. Figure 5 shows an example screenshot of the tutoring system, which provides participants with lists of the inference rules and strategies. After users select one from the lists, the system automatically runs the rules and presents the inference result. The system scaffolds the participants by giving help information about the selection of the rules and strategies and presents the candidates of the rules that should be applied in a given situation.

The LOS was controlled by the presented hint information. In the high LOS condition, the system presented both applicable candidates (rules and strategies) and propositions to which the rules should be applied. In the low LOS condition, the system only presented a set of inference rules; no candidates were presented. The participants had to select an adequate rule from the list by themselves without system support. A high LOS means that the participants were given direct help that guides them to a determined behavior.

### Participants and Procedure

Twenty-nine participants joined our experiment. 13 and 16 were assigned to the high and low LOS conditions, respectively. The experiment was performed over three weeks in an introductory cognitive science class.

In the first week, the participants learned the basics of formal inference systems and ND as an example of the systems.

In the second week, the first half of the learning phase was performed where the participants learned the four basic inference rules. In this class session, all participants learned in the high LOS condition.

In the third week, the latter half of the learning phase followed where LOS was manipulated. The participants solved relatively complex problems for which a sub-derivation process with sub-goal setting was needed. The instructor demonstrated the solutions of two problems, and then the participants solved Problems 1 to 4 with the tutoring system. In the class, the participants were divided into two groups: high LOS and low LOS. After the learning phase, two posttests were performed. Posttest 1 was identical to Problem 2, which they solved in the learning phase, and Posttest 2 as a transfer problem was a new challenge for the participants.

### Result

The optimal steps for a solution are determined in TOH. However, in the solutions of some ND problems, various reasoning paths are rational; therefore we used the average time for solving each problem in the second half of the learning phase as a problem-solving performance measure. Figure 6 shows the result. The solution time was shorter in the high LOS group than in the low LOS group when solving Problems 3 and 4. This result is consistent with our prediction.

Figure 7 shows the time for deciding and implementing an inference rule to forward reasoning. The decision time was shorter in the high LOS group than in the low LOS group when solving Problems 3 and 4. This result is consistent with our prediction.

Next, we used the scores, i.e., the ratio of successfully solved tests, in the posttest as a learning performance measure. Figure 8 shows the result, indicating that when solving Posttest 2, more participants in the low LOS group reached the solution than in the high LOS group, confirming our prediction. This effect was only observed in solving the transfer problems, but not in the repeated problems. This result is consistent with earlier experimental studies, confirming that delayed and lowering supports make positive effects, especially in solving transfer problems (Schroth, 1992, 1997).

### Discussion and Conclusions

The assistance dilemma hypothesizes an optimum point of learning effects as a function of cognitive load. Koedinger et al. (2008) indicated two dimensions of assistance: the practice spacing dimension and the example-problem dimension (Koedinger, Pavlik, McLaren, & Alevan, 2008). They demonstrated a reverse U-shape learning curve on the two dimensions. We conceptualized such a learning effect curve with a problem-solving performance curve (Figure 9). As the support level increases, the problem-solving performance is gradually promoted; however the learning effect reaches maximum at a specific support level and decreases from the point.

When comparing this framework with the results of our two experiments, note that in Experiment 1, the results indi-

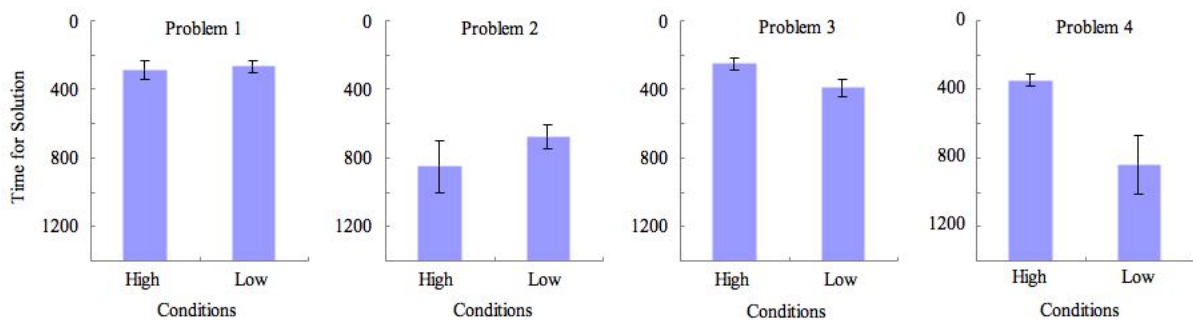


Figure 6: Average solution times for solving problems in learning phase (ND). The value of vertical axis is reversed to represent higher values as high problem-solving performances. T-tests show a marginal significant difference between high and low conditions in Problem 3 ( $t(22) = 1.92, p = 0.07$ ) and a significant difference in Problem 4 ( $t(15) = 2.70, p < 0.05$ ), but no differences in Problems 1 and 2 ( $t(25) < 1, n.s.$ ;  $t(24) = 1.14, n.s.$ ).

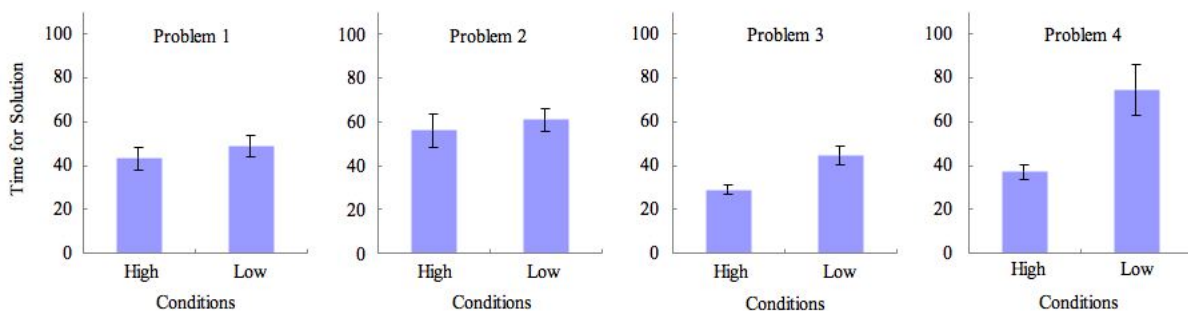


Figure 7: Average time for deciding inference rule (ND). T-tests show a marginal significant difference between high and low conditions in Problems 3 ( $t(22) = 2.55, p < 0.05$ ) and 4 ( $t(25) = 2.98, p < 0.01$ ), but no differences in Problems 1 and 2 ( $t(25) < 1, n.s.$ ;  $t(24) < 1, n.s.$ ).

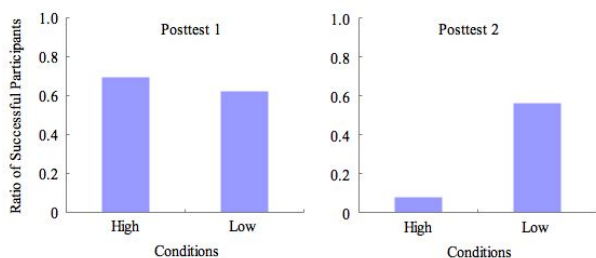


Figure 8: Ratio of successful participants (ND). Chi square tests show a significant difference between high and low conditions in Posttest 2 ( $\chi^2(1) = 7.49, p < 0.01$ ), but no difference in Posttest 1 ( $\chi^2(1) < 1, n.s.$ ).

cated in Figures 2 and 4 demonstrated this pattern, controlling the support level from the highest to the lowest on the diagram. But in Experiment 2, the results, as indicated in Figures 6 and 8, only demonstrated the left side of the pattern: control from the highest to the mid level. Our hypothesis was that a high level of support activates participant orientation to

the problem-solving goal and promotes the problem-solving performance, but reduces the priority of attaining the learning goal and decreases the learning effects. This hypothesis is consistent with the left part of Figure 9. On the right side, meaning no or a very low LOS, both the problem-solving performance and the learning effect decreased. This pattern suggests two interpretations. One is that in the right side situation, even if the participants set their goal to learning in the learning phase, they might not be able to decide what to do next and may make enormous errors, resulting in low learning effects. The other interpretation is that the participants give up the attainment of the learning goal because they face difficulties in learning without support. In the current study, we could not decide which explanation is better. Future work will address this issue.

We discussed a tradeoff between problem-solving and learning goals with the degree of support in the learning phase. This tradeoff issue appears in various research fields. For example, the effect of goal specificity has been investigated (Burns & Vollmeyer, 2002; Sweller, 1988). Participants often neglected to consider the theories or rules behind phenomena when they aimed for a specific goal. That is,

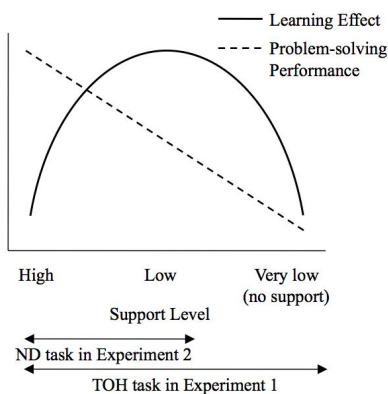


Figure 9: Conceptualized diagram of assistance dilemma and relation of problem-solving and learning goals.

they tended not to search in a hypothesis space, because they concentrated on a search in an instance space to achieve the goal. Consequently, they could not find any rules or underlying mechanisms of the task. Goal specificity studies have indicated that this tendency can be controlled by manipulating goal specificity. Specific goals are direct and immediate; therefore the degree of goal specificity is considered consistent with the levels of support in the current study. The results of our two experiments are consistent with the findings observed in many experiments conducted in the context of goal specificity studies.

Similar to our definition of the levels of support, in studies on automation usage, Sheridan & Verplank indicated ten grades of automation levels (Sheridan & Verplank, 1978). The highest level, Level 10, means that the computer acts entirely autonomously, and the lowest level, Level 1, means that a human does everything. Lin, et al. conducted a micro-world experiment where the participants controlled an atomic power plant under various levels of automation (Lin, Yenn, & Yang, 2010). Medium levels of automation maximized the participants' operations. The most important objective in the use of automation systems is stable manipulation while using the systems; therefore, the tradeoff issue of the two goals might not appear. However, researchers have pointed out the possibility that the continuous usage of automation systems may sometimes cause serious damage when the automation support is removed. For example, Parasuraman et al. argued that stable automation systems produce automation-induced complacency (Parasuraman, Molloy, & Singh, 1993; Molloy & Parasuraman, 1996). They demonstrated in a laboratory setting that operator detection of automation failures was substantially worse for constant-reliability than for variable-reliability (unstable) automation. As we mentioned, in the learning context, the problem-solving performance was measured with learning system support; on the other hand, the learning effect was usually tested without external support in posttests. In this sense, the complacency problem that

emerges when automation breaks down can be understood based on the tradeoff issue of the two goals.

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