Can tutored problem solving benefit from faded worked-out examples?

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Abstract

Although problem solving supported by Cognitive Tutors has been shown to be successful in fostering initial acquisition of cognitive skills, this approach does not seem to be optimal with respect to focusing the learner on the domain principles to be learned. In order to foster a deep understanding of domain principles, we developed a Cognitive Tutor that contained, on the basis of the theoretical rational of example-based learning, faded worked-out examples. We conducted two experiments in which we compared the example-enriched Cognitive Tutor with a standard Cognitive Tutor. In Experiment 1, we found no significant differences in the effectiveness of the two tutor versions. However, the example-enriched Cogntive Tutor was more efficient (i.e., students needed less learning time). A problem that was observed is that students had great problems in appropriately using the example-enriched tutor. In Experiment 2, we, therefore, provided students with additional instructions on how to use the tutor. Results showed that students in fact acquired a deeper conceptual understanding when they worked with the example-enriched tutor and they needed less learning time than in the standard Tutor. The results are suggestive of ways in which instructional models of problem-solving and example-based learning can be fruitfully combined.

Introduction

Cognitive Tutors – an intelligent tutoring system – have been proven to be very effective in supporting students' learning in a variety of domains, including mathematics, computer programming, and genetics (for an overview, see Anderson, Corbett, Koedinger, & Pelletier, 1995; Koedinger & Corbett, 2006). On the basis of an online assessment of the student's learning, they provide individualized support for guided learning by doing. Specifically, the tutor selects appropriate problems, give just-in-time feedback, and presents hints. Despite their effectiveness, a shortcoming of the tutors is that they primarily focus on students' problem-solving and do not necessarily support a conceptual understanding about the domain to be learned.

Previous research has attempted to address this limitation by introducing self-explanation prompts to the students who work with the tutor. The prompts require students to provide an explanation for each of the solution steps undertaken by making an explicit reference to the underlying principle. Empirical findings show that this instructional approach makes the cognitive tutor indeed more effective (Aleven & Koedinger, 2002). However, from a cognitive load perspective (e.g., Sweller, van Merriënboer, & Paas, 1998), it might be objected that the technique is nevertheless suboptimal because the induction of self-explanation activities in addition to problem solving puts fairly high demands on students' limited cognitive capacity, particularly at the early stages of skill acquisition. Therefore, working with the tutor might be further improved by reducing the cognitive load of the students' mind (e.g., van Merriënboer, Kirschner, & Kester, 2003). This would allow students to have more attentional capacities available for engaging in meaningful learning activities.

Against this background, it might be sensible to provide students with worked-out examples. The instructional model of example-based learning developed by Renkl and Atkinson (in press) suggests that learners gain a deep understanding of a skill domain when they receive worked-out examples at the beginning of cognitive skill acquisition. A worked-out example consists of a problem formulation, solution steps, and the final solution. When studying worked-out examples instead of solving problems, the learners are freed from performance demands and they can concentrate on achieving a deep understanding. Assuring that learners have a basic understanding before they start to solve problems should help them to deal with the problem-solving demands by referring to already acquired principles, which should prevent them from using only shallow strategies, such as means-end analysis or copy-and-adapt strategies (e.g., using the solution of a previously solved problem that is adapted with respect to the specific numbers). The use of principles enables learners to deepen their knowledge by applying the principles to new problems and, in addition, will cause them to notice gaps in their principle-related understanding when they reach an impasse (cf. VanLehn et al., 2005).

There is ample empirical evidence showing that learning from worked-out examples leads to superior learning outcomes as compared to the traditional method of problem solving (for an overview, see Atkinson, Derry, Renkl, & Wortham, 2000). However, it is important to note that studying worked-out examples loses its effectiveness with increasing expertise. In later stages of skill acquisition, the skillful execution of problem-solving activities plays a more important role because emphasis is put on increasing speed and accuracy of performance (Renkl & Atkinson, 2003). For example, Kalyuga, Chandler, Tuovinen, and Sweller (2001) found that learning from worked-out examples was superior in the initial phase of cognitive skill acquisition. However, when learners already had a basic understanding of the domain, solving problems proved to be more effective than studying examples (*expertise reversal effect*; Kalyuga, Ayres, Chandler, & Sweller, 2003). Therefore, Renkl and Atkinson (2003) proposed a fading procedure in which problem-solving elements are successively integrated into example study until the learners are expected to solve problems on their own. First, a complete example is presented. Second, a structurally identical incomplete example is provided in which one single step is omitted. In the subsequent isomorphic examples, the number of blanks is increased step by step until just the problem formulation is left, that is, a problem to be solved. Hence, by gradually increasing problem-solving demands, the learners should retain sufficient cognitive capacity to successfully cope with these demands and, thereby, to focus on domain principles and on gaining understanding. In a number of experiments, Renkl and colleagues provided empirical evidence for the effectiveness of a smooth transition from example study to problem solving (e.g., Atkinson, Renkl, & Merrill, 2003; Renkl, Atkinson, & Große, 2004).

Against this background, we expected that a Cognitive Tutor that not only prompts students to engage in self-explaining but also provides them with gradually faded worked-out examples should foster students' learning, particularly with respect to their conceptual understanding. In addition, the empirical results on the *worked-example effect* (positive effect of studying examples) also leads to the expectation that the learners need less study time (cf. e.g., Sweller & Cooper, 1985) when in an example-enriched Cognitive Tutor as compared to the standard version. Accordingly, we hypothesized that a combination of example study and tutored problem solving would be more effective and more efficient than tutored problem solving alone. As state-of-the-art implementation of example-based learning, the Cognitive Tutor contained faded worked-out examples that structured the transition from example study in earlier stages of skill acquisition to problem solving in later stages.

In this article, we present two experiments in which we investigated the question whether an 'example-enriched' Cognitive Tutor would lead to superior learning when compared with a standard version of a Cognitive Tutor. For this purpose, we used the Cognitive Tutor Geometry. Students were asked to work on geometry problems that required them to apply different geometry principles.

Experiment 1

Method

Sample and Design

Fifty students from a German high school, 22 eighth-grade students and 28 ninth-grade students, participated in the experiment (average age: 14.3 years; 22 female, 28 male). The students were randomly assigned to one of the two experimental conditions. In the experimental condition (*example condition*; $n = 25$), students worked with a Cognitive Tutor that presented faded worked-out examples. In the control condition (*problem condition*; $n = 25$), the students worked with a standard version of the tutor in which students received no faded worked-out examples.

Learning Environment – The Cognitive Tutor

The students used an updated version of the Cognitive Tutor Geometry. In this version, self-explanation prompts were employed (Aleven & Koedinger, 2002). In addition, the information such as text and diagrams was presented in a single worksheet (i.e., in an integrated format). For the purpose of comparing worked-out examples with problem solving, the integrated format of the tutor was important because example-based learning might be only more effective than problem solving when the examples are not displayed in a 'split source format' (i.e., examples where related information such as text and schematics or diagrams is presented separately¸ cf. Tarmizi & Sweller, 1988). Thus, this Cognitive Tutor version allowed a fair and a state-of-the-art implementation of worked-out examples.

In general, Cognitive Tutors employ two algorithms to support learners. These algorithms are called 'model tracing' and 'knowledge tracing'.

Model Tracing In order to provide appropriate just-in-time feedback and corrective hints, the Cognitive Tutor relies on a computational model of the problems that the students have to solve. The model not only represents the domain specific knowledge that is necessary to solve problems but also problem-solving knowledge and skills that are typical for novices (Koedinger & Corbett, 2006). Single problem-solving steps (so -called *knowledge components*) are represented as production rules (i.e., if-then rules that link internal goals with new goals or external cues with actions). All user entries are interpreted relative to this model. In case of an answer that refers to a valid production rule, the answer is just marked as 'correct'. In case of an answer that relates to an invalid rule, a referring hint is presented. In case of an answer that is not related to any production rule, the answer is marked as 'false'.

Knowledge tracing In full-scale Cognitive Tutors, instruction is further individualized by selecting problems based on a model of the students' present knowledge state that is constantly updated through a Bayesian process called 'knowledge tracing' (Corbett & Anderson, 1995). Hence, depending on the student's knowledge, additional problems might be presented in order to foster students' learning. However, in order to keep the number and order of problems constant across participants and experimental conditions in our experiments, we did not use the knowledge tracing mechanism. That is, in both experimental conditions, students worked with a version of the geometry tutor that provided individualized feedback on the basis of the model tracing procedure. However, all students worked on the same set of problems that were presented in the same order (i.e., no selection of problems on the basis of the knowledge tracing algorithm).

Learning material In total, students were asked to work on seven problems. The first three problems required the application of only one geometry principle. In order to solve the last four more complex problems, it was necessary to apply these geometry principles in combination. In the *problem condition*, solving a problem required students (a) to enter a numerical value in an entry field that was embedded in a graphical representation of the problem (in a worksheet), and (b) to justify each given numerical answer. This justification could be entered either by typing the referring principle into a text entry field (next to the numerical value entry field), or by selecting a principle from a glossary that contained a list of all principles used in the unit (i.e., explanation by reference). The combination of entering a value and providing a justification is called a learning event. In the following, an example of a learning event is given. Given the value of an angle $\angle ABC = 145°$, a student has to figure out the value of the supplementary angle $\angle ABD$. The correct entry would be $\angle ABD = 35°$, because $\angle ABD = 180° - \angle ABC$. After entering the value (or the equation leaving the computation to the tutor) the student has to justify (i.e., to explain) this numerical answer in a second step (in this case, a valid explanation would be 'supplementary angles').

In the *example condition*, students were asked to study worked-out examples that addressed the same problems that students in the problem condition were solving. A worked-out example provided the students with the numerical value (to be figured out in the problem condition) together with the necessary solution steps. The examples were gradually faded out according to the fading scheme described in Table 1. The table shows that the application of the principle in each of the first three problems was illustrated by a worked-out example. Also, worked-out examples were used for the fourth problem that required the application of the three principles in combination. In the subsequent problems, however, each of the principles was gradually faded out until just the problem formulation was left (problem 7).

Table 1: The sequencing of problems and fading of worked-out steps.

| Problems | Examples | | | Problem solving | | |
| | Principles | | | | | |
	P1	P2	P3	P1	P2	P3
P1	W			S		
P2		W			S	
P3			W			S
P4	W	W	W	S	S	S
P5	W	W	S	S	S	S
P6	W	S	S	S	S	S
P7	S	S	S	S	S	S

Note. W stands for worked-out examples and S for problem solving.

In order to hold the self-explanation activities across the two experimental conditions constant, students in both versions of the Cognitive Tutor were asked to provide justifications for all solution steps that were performed (in the problem condition and later also in the example condition) or provided by a worked-out step (only in the example condition). Hence, when working on the first four problems, students in the example condition had to enter justifications for the numerical answers that were provided in the worked-out examples by the tutor. Like in the problem condition, the justifications could be typed in or selected from the glossary. From problem five to problem seven, problem-solving demands in the example condition were gradually increased. Hence, students were required not only to give justifications but also to solve the problem on their own.

Instruments

Pretest A short pretest on circles geometry containing 4 problems examined the topic-specific prior knowledge of

the students. The maximum score to be obtained in the pretest was 12 points (3 points for each problem that was solved in a totally correct way).

Post-test The post-test that measured students' learning consisted of 13 questions. Two questions required the students to solve problems that were isomorphic to the problems previously presented by the Cognitive Tutor (near transfer items). In addition, 2 questions were devised to test students' ability to apply their knowledge about the geometry principles to new geometry problems (far transfer items). As both transfer scores correlated with .69 ($p < .001$), we aggregated them to an overall transfer score. Finally, 9 questions assessed the conceptual understanding that students acquired with the help of the tutor. Students were asked to explain the geometry principles (a maximum of 22 points could be obtained).

Procedure

The experimental sessions lasted, on average, 90 minutes and were divided into three parts: pretest and introduction, tutoring, and post-test. In the pretest and introduction part, students were asked to complete the pretest measuring their prior knowledge. Afterwards, they read an instructional text that provided them with information about the rules and principles that were later addressed by the Cognitive Tutor. In addition, they received a brief introduction on how to use the tutor. In the tutoring part, students worked either with the standard Cognitive Tutor Geometry unit or with the example-enriched version. In the post-test part, all students answered the transfer questions and the questions assessing their conceptual knowledge.

Results

First, we analyzed students' prior knowledge in order to assure that the experimental conditions did not differ with respect to this important learning prerequisite. There were no significant differences between the experimental groups, $t(48) = -0.75$, $p > .05$. The low test scores obtained in the pretest (cf. Table 2) indicate that students in both experimental conditions were in fact in the initial phase of skill acquisition.

In a second step, we analyzed whether learning with a combination of example study and tutored problem solving was better than tutored problem solving alone. We found, however, no significant differences in students' learning outcomes, neither for conceptual knowledge, $t(48) = -0.11$, $p > .05$, $r = .02$, nor for transfer, $t(48) = 0.22$, $p > .05$ $r = .03$. Hence, both versions of the cognitive tutor were similarly effective.

In a last step, we examined how efficiently students worked with the tutor. For this purpose, we compared the time that students spent working on the problems or examples provided by the tutor. The analysis revealed significant time on task differences, $t(48) = -3.11$, $p < .001$ (one-tailed), $r = .41$. Students in the problem condition spent more time for learning than students in the example condition (cf. Table 2).

Table 2: Means and standard deviations of pretest and post-test scores, learning time, and learning efficiency for the experimental conditions in Experiment 1.

Variable	Example		Problem	
	M	*SD*	*M*	*SD*
Pretest[a]	1.54	1.31	1.82	1.35
Learning time[b]	30.0	6.56	35.4	5.72
Conceptual knowledge[c]	.54	.21	.54	.21
Transfer[c]	.12	.12	.11	.13
Conceptual knowledge acquisition efficiency[d]	0.28	1.13	-0.28	1.13
Transfer acquisition efficiency[d]	0.31	1.28	-0.31	1.11

Note. [a]A maximum of 12 points could be achieved. [b]Learning time in minutes. [c]Solution rates in %. [d]Efficiency = ($z_{Posttest}$-$z_{Learning time}$)/SQRT(2).

In order to quantify the differences in efficiency, we adopted the efficiency measure developed by Paas and colleagues (Paas, Tuovinen, Tabbers, & Van Gerven, 2003; Paas & Van Merriënboer, 1993). This measure relates their performance in terms of learning outcomes to their mental effort in terms of cognitive load as measured. More specifically, the efficiency score equals to the difference of z-scores of mean performance and effort measures (i.e., $z_{performance}$-z_{effort}) divided by the square root of two. The division by the square root of two allows to express efficiency as the perpendicular distance to a diagonal line (through the origin of a Cartesian axis) that represents a balanced ratio of effort and performance. For our purposes, we related performance in terms of the acquisition of conceptual knowledge and of transferable knowledge respectively to effort in terms of time on task (i.e., the time spent working on the problems). This relationship is depicted in the following formula:

$$\text{learning efficiency} = (z_{Posttest}\text{-}z_{TimeOnTask})/\sqrt{2}$$

When applying this efficiency formula to our data, we found significant differences between the experimental conditions for both the efficiency of conceptual knowledge acquisition, $t(48) = 1.73$, $p < .05$ (one-tailed), $r = .24$, and the efficiency of the acquisition of transferable knowledge, $t(48) = 1.82$, $p < .05$ (one-tailed), $r = .25$, which both represent medium sized effects (see Table 2).

Discussion

Both tutored problem-solving and learning with a smooth transition from worked-out examples to problem solving led to comparable levels of conceptual and procedural knowledge (in terms of near and far transfer). However, about the same learning outcomes were achieved in shorter learning times in the example-enriched Cognitive Tutor. Accordingly, the efficiency of learning was superior in this latter learning condition.

The lacking difference in effectiveness might be explained by the fact that even the standard version of the Cognitive

Tutor is very supportive. Thus, there might not have been much room for improvement (cf. Koedinger & Aleven, in press). Both versions of the tutor provided corrective feedback on errors and induced students to engage in self-explaining activities. However, students in both experimental conditions achieved relatively low post-test scores making this explanation not very likely.

Informal observations and analyses of the log-file data suggested that students had difficulties in working with the Cognitive Tutor. These problems were clearly more pronounced in the example condition than in the problem condition. Although students received an instruction on how to use the tutor, students in the example condition in particular had trouble in understanding the purpose of the worked-out examples. One severe and persistent misunderstanding referred, for example, to the justifications that students had to give for a solution step. In the majority of cases, the students assumed that they had to enter the justification 'given' (because the numerical value had been provided by the tutor) instead of the mathematical principle relevant to the task at hand.

In order to examine whether students' problems in using the Cognitive Tutor, especially working on the worked-out geometry tasks, diminished possible differences between the two experimental conditions, we conducted another experiment. In this experiment, we gave the students more detailed and specific instructions on how to use the tutor.

Experiment 2

In the second experiment, we provided the students in both experimental conditions with more specific instructions prior to using the tutor. In addition, when students worked on the two warm-up examples provided by the tutor, they received, in case of problems in understanding, scaffolding from the experimenter.

Method

Experiment 2 was identical to Experiment 1 with respect to the experimental set up, the learning environment, and the instruments (e.g., pretest and post-test). Yet, the experiment was different with respect to the level of detail of the instruction and scaffolding provided in advance, as explained before. In addition, students in experiment 2 participated in individual sessions in the study, whereas Experiment 1 took place in a group session format.

Sample and Design

In Experiment 2, 16 ninth-grade students and 14 tenth-grade students of a German high school (average age: 15.7 years; 27 female, 13 male) took part. Like in experiment 1, one half of the students were assigned to the example condition (n = 15) and the other half to the problem condition (*n* = 15).

Procedure

The procedure was almost identical to Experiment 1. The only difference was that students in both experimental conditions received more detailed instructions on how to use the instructional features of the Cognitive Tutor.

Results and Discussion

In a first step, we analyzed students' prior knowledge. Again, there were no significant differences between the experimental conditions, $t(28) = 0.27$, $p > .05$ (cf. Table 3). We then examined whether students in the example condition benefited more from the example-enriched Cognitive Tutor than students in the problem condition. With regard to students' conceptual understanding, we indeed found an advantage of the example condition over the problem condition, $t(28) = 1.85$, $p < .05$ (one-tailed), $r = 0.33$ (medium sized effect). However, again there were no significant differences in students' transfer knowledge, $t(28) = -0.61$, $p > .05$, $r = 0.11$.

Table 3: Means and standard deviations of pretest and post-test scores, learning time, and learning efficiency for the experimental conditions in Experiment 2.

Variable	Example		Problem	
	M	*SD*	*M*	*SD*
Pretest[a]	1.67	1.88	1.50	1.47
Learning Time[b]	30.0	6.48	39.2	9,31
Conceptual knowledge. [c]	.61	.14	.50	.16
Transfer [c]	.19	.22	.24	.25
Conceptual knowledge acquisition efficiency [c]	0.58	0.90	-0.58	0.94
Transfer acquisition efficiency [d]	0.31	1.28	-0.31	1.11

Note. [a]A maximum of 12 points could be reached. [b]Learning time in minutes. [c]Solution probability (in percent). [d]Efficiency = $(z_{Posttest} - z_{Learning time})/SQRT(2)$.

In a last step, we computed the efficiency of students' using the Cognitive Tutor. The differences found in experiment 1 could be replicated. This time, the differences were even more pronounced. Again, students in the problem condition spent more time working with the tutor than students in the example condition, $t(28) = -3.14$, $p < .001$ (one-tailed), $r = 0.51$ (large sized effect). Hence, when we related performance in terms of the acquisition of conceputal knowledge to the effort in terms of time on task, we obtained a large effect, $r = 0.55$, $t(28) = 3.48$, $p < .001$ (one-tailed). The efficiency of transferable knowledge acquisiton failed to reach the level of significance, $t(28) = 1.44$, $p = .08$ (one-tailed), $r = 0.26$.

General Discussion

In the two experiments, we compared a standard Cognitive Tutor with an example-enriched Cognitive Tutor. Both versions of the tutor offered corrective feedback and self-explanation prompts. We found first evidence that a state-

of-the-art implementation of a faded worked-out steps procedure can lead to a deeper conceptual understanding than problem solving alone. In addition, the results on learning time and efficiency showed hat example-based learning is less time consuming without a loss (Experiment 1) or even a gain in performance (Experiment 2).

Nonetheless, in contrast to previous research (cf. Atkinson et al., 2000), we found no benefits of example-based learning for students' acquisition of procedural skills. The results showed that in both experimental conditions, students' performance in the transfer knowledge test was quite similar. Note, however, that previous studies merely compared example-based learning with largely unsupported problem solving, that is, in previous research students who engaged in problem solving received no substantial instructional support. In contrast, the standard Cognitive Tutor provided students with a substantial amount of support by hints and corrective feedback. Therefore, it was comparatively difficult to find incremental effects on students' performance when additionally using worked-examples.

Moreover, it might be speculated that the use of examples in the Cognitive Tutor might be further optimized. Although the effectiveness of faded examples has been shown in previous and in our experiments, faded examples could be even more beneficial to learning if they took into account the individual prerequisites of the students. It is plausible to assume that students might largely differ in the speed and accuracy with which they learn domain principles. Therefore, it would be sensible to adapt the speed of fading worked-out steps to the students' individual learning progress. We will conduct an experiment in which we examine the surplus value of a fading procedure that dovetails with the students' specific needs.

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