The Impact of Explicit Strategy Instruction on Problem-solving Behaviors across Intelligent Tutoring Systems

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Abstract

Explicit instruction of a problem-solving strategy improved students' performance in the domain where it was taught and in a second domain where it was not taught. Since the two domains, probability and physics, share no overlapping domain principles, it seems likely that the problem-solving strategy itself was transferred from one domain to the other. We analyzed the computer logs to identify the strategies employed in the physics domain. On hard problems the Strategy group did in fact employ the taught strategy in question. However on easier problems they appeared to abandon the strategy in favor of more sophisticated strategies. We conjecture that explicit strategy instruction increased students' focus on domain principle acquisition, which in turn accelerated their learning to the point where they no longer needed to use the taught strategy and instead could use more expert-like strategies. However, when they got stuck, they fell back on the taught strategy. That is, explicit strategy instruction appears to act as surprisingly effective scaffolding for domain principle acquisition.

Keywords: Problem-solving strategy, Acceleration of future learning, preparation for learning, cross-domain transfer.

Introduction

A task domain is *deductive* if solving a problem requires producing an argument, proof or derivation consisting of one or more inference steps, and each step is the result of applying a general domain principle, operator or rule. Deductive task domains, such as physics and geometry, are common parts of mathematical and scientific courses. Two common problem-solving strategies in deductive domains are *forward chaining* (FC) and *backward chaining (BC)* (Russell & Norvig, 2003). In FC, the reasoning proceeds from the given propositions toward the goal. The solver starts with a set of known propositions, applies a principle to some subset of them, produces at least one new proposition, and continues doing this until the problem is solved. BC is *goal-directed*. It works backward from a goal state to the known state. At any time, it backward-applies a deductive rule that can infer the current goal from some subgoals in the context of the current state. It then picks a subgoal as its current goal, and repeats this process until the known state is reached. This procedure produces a plan, which is then executed.

FC and BC have been widely used in computer science; however, they are rarely taught to human problem solvers and are seldom observed in a pure form in natural human problem solving. Early studies of experts and novices suggested that novices used BC and experts used FC (Larkin et al. 1980), but later studies showed that both used fairly similar mixtures (Priest & Lindsay 1992). Eventually, work in this area diminished because it appeared that most human solvers use a mixture of strategies, analogies with past solutions, heuristics, and many other kinds of knowledge in order to guide their problem solving.

Although neither experts nor novices seem to use FC and BC in their pure form, the strategies' success in guiding computer problem solvers suggests that teaching students to use pure FC or BC might improve their problem-solving abilities. There have been several tests of this hypothesis.

Sweller and his colleagues conducted a series of studies comparing the learning of students who were or were not required to use FC (Owen & Sweller 1985; Tarmizi & Sweller 1988). Students who were required to use FC to solve problems learned more than those who could use unconstrained mixture of strategies. This suggests that "teaching" students a single problem-solving strategy improves learning. However, the number of inferences made by the FC students is generally larger than the number of inferences made by those who use the usual unconstrained mixture of strategies. Thus, the FC students could have benefited simply from having more practice in applying the domain principles. Indeed, when the study was modified so that students in both conditions applied the same number of domain principles, they learned the same amount (Sweller, 1988). Thus, although these studies are consistent with the hypothesized benefits of explicit strategy instruction, there are other explanations for the results as well.

Trafton and Reiser (1991) tested the benefits of explicit strategy instruction in a subdomain of computer programming, wherein students had to compose and combine primitive functions to produce a more complex function specified by the experimenter. Three forms of instruction were compared based on the way in which the function was to be composed: forward-only, backward-only or freely. After 13 training problems completed in less than one hour, all three groups achieved the same learning gains. The study did not find benefits on learning gains for explicit instruction in a problem-solving strategy. Although it is always hard to interpret a null result, it could be that the task domain was too simple, about 4 minutes per problem, to allow a problem-solving strategy to demonstrate its benefits.

Scheines and Sieg (1994) gave students over 100 training problems in sentential logic over a 5 week period. Students were divided into three groups: one was taught and required to use FC; another was taught BC and required to use it; and a control group was not taught any strategy and operated freely. After five weeks training, no significant differences were found among the three groups on the mid-term exam (post-test). When the FC and BC groups were aggregated as a one-way strategy condition, there were still no significant differences between them and the control group on post-test scores. However, contrary to our hypothesis, the control group gained more than the one-way strategy students on difficult problems, where one would expect an explicit search strategy to be especially helpful. The experiment suggested that constraining students to use just one strategy may actually harm their performance. However, Sieg and Byrnes (1998) discovered a more efficient strategy that used FC on certain inference rules and BC on others. They hypothesized that the control students' superiority could have been due to their use of elements of this strategy. This is consistent with the fact that the control students used BC on 46% of their moves and FC on the rest. Sieg's group is currently investigating the effects of explicitly teaching students this strategy (Sieg, personal communication, December 2006).

VanLehn et al. (2004) compared an explicitly taught version of BC to unconstrained problem-solving. On some post-test measures, the students who were explicitly taught the strategy scored higher than those who were not taught a strategy and could solve problems in any order. However, on other measures, the two groups did not differ. Overall, performance on the post-test was quite poor, suggesting a floor effect—the post-test was too difficult for both groups.

Although there have been other studies of explicit strategy instruction, they mostly involved inductive rather than deductive problem solving. For instance, students who were taught inquiry strategies, such as CVS (control-of-variables strategy) or VOTAT (Vary One Thing At a Time), not only employed them more frequently and consistently, but they also induced more domain knowledge than students who were not taught any inquiry methods (Vollmeyer et al. 1996; Klahr & Nigam 2004; Toth et al. 2000).

In summary, the studies of deductive problem-solving strategies have primarily shown how difficult such studies are to conduct, as they have been plagued with confounded designs (Owen & Sweller 1985; Tarmizi & Sweller 1988; Sweller, 1988), null effects (Trafton & Reiser 1991), teaching of suboptimal strategies (Scheines & Sieg 1994), and floor effects (VanLehn et al. 2004). Despite all this work, we still lack an unequivocal answer to the simple question: Given that BC, FC, and other domain-general strategies work so well for computer problem solving, should we teach them to human students?

This study was designed to test two hypotheses: (1) because FC and BC benefit computer problem solving by reducing search space, but search occurs only on some problems, we hypothesize that explicit strategy instruction will cause increased search efficiency on problems that require multiple principle applications, but not on single-principle problems. (2) Our second hypothesis, again inspired by computer problem solving, is that the explicitly taught strategy is domain general. That is, if students are taught a strategy in one domain, they will be able to use the strategy in a second domain without any further instruction.

As the earlier work shows, choice of task domain can affect the ability to test the impact of strategy on learning. In order to assess inter-domain transfer, we needed two domains that share a problem solving strategy. The domains should be complex enough that following the strategy visibly improves problem solving on multi-principle problems, thus allowing us to detect the strategy's usage. The task domains chosen were probability and introductory physics, because earlier work (e.g., VanLehn et al., 2004) suggested they had the properties listed above.

As a brief overview, the experiment proceeded as follows. During probability instruction, students studied 10 principles of probability, such as Bayes rule. The Strategy students were trained on a tutoring system that explicitly taught the Target Variable Strategy (TVS), a domain-general BC strategy (VanLehn et al. 2004); while the No-strategy students were trained on another tutoring system without any explicit strategy instruction. During the subsequent physics instruction, students studied 10 principles of work and energy, such as conservation of total mechanical energy. Both the Strategy and No-strategy students were trained on the same physics tutoring system, which did not teach any strategy.

If our hypotheses are correct, the Strategy students should outperform the No-strategy students in learning both domains. Moreover, if this difference is due to increasing the efficiency of problem solving, as hypothesized, then it should show up only on multi-principle problems, where the strategy actually does increase efficiency. For single-principle problems, the Strategy and No-Strategy students should perform identically.

As reported earlier (Chi & VanLehn, 2007), teaching the TVS caused acceleration of learning in both domains and unexpectedly on all types of problems. The Strategy students gained significantly more than the No-strategy ones on both single-principle problems and multi-principle problems in both domains. Moreover, the effects were large: Cohen's d was 1.17 for probability post-test scores and 1.28 for physics post-test scores. To investigate why this welcome benefit occurred, we analyzed computer logs of students' problem-solving behavior in order to determine whether the Strategy students were applying the TVS during the physics instruction where no strategy was taught.

Methods

Participants

We recruited 91 college students who received payment for their participation. They were required to have basic knowledge of high-school algebra, and not to have taken college-level statistics or physics courses. Students were randomly assigned to the two conditions. Each student took from two to three weeks to complete the study. Because of the winter break and length of the experiment, only 44 participants completed the experiment. Two students were eliminated from the final sample size (N = 44) because of a perfect score on the probability pre-test and a lack of time consistency, respectively. Of the remaining 42 participants (59.5% female), 20 were Strategy students and 22 were No-strategy students.

Materials:

Three tutoring systems: Two were used for probability instruction, Pyrenees and Andes-probability, and one for physics, Andes-physics. Apart from domain knowledge, Andes-probability and Andes-physics were identical. Pyrenees explicitly taught the TVS and required students to follow it. Andes provided no explicit strategic instruction nor did it require students to follow any particular strategy. Students using Andes could input any entry, and Andes would color it green if it was correct and red if it was incorrect. An equation was considered correct if it was true, irrespective of whether it was useful for solving the problem. Students could enter an equation that was an algebraic combination of several principle applications on Andes but not on Pyrenees.

Besides providing immediate feedback, both Pyrenees and Andes provided help when students asked. When an entry was incorrect, students could either fix it on their own or ask for *what's-wrong help*. When they do not know what to do next, they could ask for *next-step help*. Pyrenees and Andes gave the same *what's-wrong help*, but their next-step help differed. Because Pyrenees required students to follow the TVS, it knew exactly what step the student should be doing next so it gave specific hints. In Andes, on the other hand, students could always enter any correct step, so Andes did not attempt to figure out the student's problem-solving plans or intentions Instead, it picked a step that it would most like to do next, and hinted that step. Both types of help were provided via a sequence of hints that gradually increased in specificity. The last hint in the sequence, called the *bottom-out hint*, told the student exactly what to do.

Procedure:

The procedure for this study had 4 main parts: Background Survey, Learning Probability, Andes Interface Training, and Learning Physics (see Table 1, left column). All the materials were online. Only the Strategy students took the third part, Andes Interface Training. Its purpose was to familiarize the Strategy students with the Andes user interface without introducing any new domain knowledge.

Learning Probability and Learning Physics had the same five phases: 1) pre-training 2) pre-test, 3) watching a video, 4) training on an ITS, and 5) post-test. We will describe each phase.

Table 1: Procedure.

	Strategy	No-strategy
Survey	Background survey	
Learning Probability	Probability pre-training	
	Probability pre-test	
	Pyrenees video	Andes-Prob. video
	Problem-solving with Pyrenees	Problem-solving with Andes-Probability
	Probability post-test	
Andes Interface Training	Andes-Probability video	
	Solve a problem with Andes-Prob.	
Learning physics	Physics pre-training	
	Physics pre-test	
	Andes-Physics video	
	Problem-solving with Andes-Physics	
	Physics Post-test	

During pre-training all students studied the domain principles. For each principle, they read a general description, reviewed some examples, and solved a series of single-principle and multi-principle problems. After solving a problem, the answer was marked correct or incorrect, and the correct solution was displayed. If students failed to solve a single-principle problem, then they were asked to solve an isomorphic one; this repeated until they either succeed in solving a problem or failed three times. On multiple-principle problems, students had only one chance to solve the problem and were not asked to solve an isomorphic problem if their answer is incorrect.

Next, students took a pre-test. Feedback on answers was not given. This was also true for the post-tests.

During phase 3, all students watched a video that covered solving a domain problem in the corresponding tutoring system. When learning probability, the Strategy students also read a text description of the TVS.

Table 2: Number of single- and multi-principle problems

		Single-	Multi-	Total
Probability	Pre-Training	14	5	19
	Pre-test	10	4	14
	Training	0	12	12
	Post-test	10	10	20
Physics	Pre-Training	11	3	14
	Pre-test	9	5	14
	Training	0	8	8
	Post-test	5	13	18

During phase 4, both conditions solved the same problems in the same order. Each main domain principle was applied at least twice. All students could access the corresponding pre-training textbook. When learning probability, the Strategy students could also access the description of the TVS.

Finally, all students took a post-test. Five of the post-test problems were isomorphic to training problems in phase 4. In addition, there were five non-isomorphic problems on the probability post-test and eight on the physics post-test.

Table 2 shows the distribution of single-principle and multi-principle problems in the experiment. Most of the multi-principle problems had dead-end search paths so that the TVS could show an advantage in search efficiency.

To summarize, the procedural difference between the two conditions were: 1) during Learning Probability, the Strategy students trained on Pyrenees while the No-strategy students trained on Andes; 2) the Strategy students learned how to use Andes' GUI before learning physics.

Results

We begin by summarizing results reported earlier (Chi & VanLehn, 2007). Despite the high attrition, the incoming student competence was balanced across conditions. There were no significant differences between the two conditions on the background survey, which included self-reported GPA and SAT scores, nor on the probability pre-training scores, nor on the probability pre-test scores. Moreover, there were no group differences on any of the 4 training times: probability pre-training, probability training, physics pre-training and physics training.

On the other hand, the two groups did differ on post-training problem-solving scores. Students' answers were scored both with and without partial credit. With a few exceptions, different scoring rubrics produced the same pattern of results. The results for the no-partial-credit rubric, which was the most objective rubric, are shown in Table 3. Numbers in the cells are the effect size. An *ms* or *ns* indicates that the difference between the means was only marginally significant or non-significant.

As shown in Table 3, the Strategy students learned more than the No-strategy ones during probability training, physics training and perhaps even physics pre-training. Moreover, the Strategy training advantage does not seem to be only due to increasing the search efficiency, as the gains appeared even on single-principle problems, which do not require any search. The learning gains on single-principle problems may have been caused by increased motivation, or increased acquisition of domain principles, or both. If it was due to motivation only, then we might see little actual use of the TVS during physics problem-solving. This possibility motivated our analysis of physics problem-solving behavior, which is presented next.

Table 3: Effect sizes of Strategy students compared to No-strategy students

Problem type		Single-	Multi-	All
Probability	Post-test	1.24	0.87	1.17
Physics	Pre-Training	0.64[1]	*ns*	*ns*
	Pre-test	*ms*	*ns*	0.69
	Post-test	1.00	1.23	1.28

[1] On single-principle problems solved correctly at the first try.

Coding categories:

Andes-Physics logged every user interface action performed by the student, including their help requests, tool usage, and equation entries. We coded each correct equation entry in the solution logs with 3 features:

Relevance: The equation was labeled relevant or irrelevant based on whether it contributed to the problem solution.

Help: The student's equation was labeled "Help" if it was entered after the student asked for help from the tutoring system. Otherwise, it was labeled "No-help".

Content: The equation's content was coded as either (1) incorrect, (2) algebraic manipulation of an existing equation, (3) repetition of an existing equation, or (4) correct equation with new physics content

Overall characterization

We first tried to characterize the overall difference in students' solutions of the physics training problems. We found that the Strategy students made significantly fewer next-step help requests than No-strategy ones on every problem, which suggested that the Strategy students may be using the TVS more frequently, and thus getting lost less frequently. However, there are other possible explanations, so we conducted several other analyses.

Based on the characteristics of the help requests, solutions were grouped into three categories, smooth, help-abuse, and rocky, which were defined as follows:

Smooth solutions included no help requests, except on problems that require more than eight principle applications, where students were permitted up to two what's-wrong help requests.

Help-abuse solutions are produced when every entry was derived from one or more next-step hints.

Otherwise, the solution was categorized as a *rocky* solution, in which, students appeared capable of solving part of the problem on their own, but needed help on the rest.

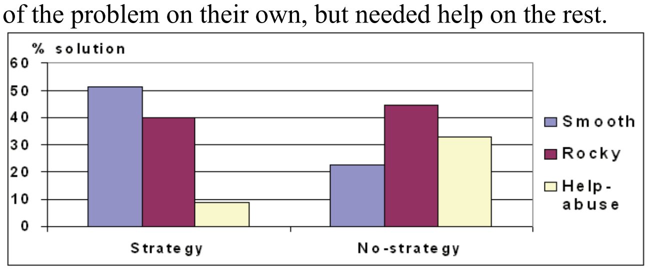

Figure 1: Solution Percentage by Type

As Figure 1 shows, there was a significant difference between two groups in the total number of help-abuse solutions, rocky, or smooth solutions: $\chi^2(2) = 41.33$, $p(\chi^2) < 0.0001$. Overall, the Strategy students had significantly more smooth solutions and less help-abuse solutions than the No-strategy ones.

The next analysis was conducted with a smaller unit of analysis: individual equations. We sought to find out how frequently students made steps toward solving the problem without any help from the tutor. In terms of the three-feature coding mentioned earlier, such an equation would be coded as "relevant", "No-help", and "correct equation with new physics content”. Thus, we called them desirable steps and we measured desirable steps ratio DSR as:

$$DSR = \frac{\text{Desirable Steps in the solution}}{\text{All Steps in the solution}}$$

As shown in Figure 2, the Strategy students have significantly higher DSR than the No-strategy ones: $t(253) = 8.09$, $p < 0.0001$. It is also true on rocky solutions alone, $t(136) = 3.27$, $p = 0.001$. These results indicate that the No-strategy students’ rocky solutions were even “rockier” than the Strategy students’. This may have contributed to their poorer learning gains.

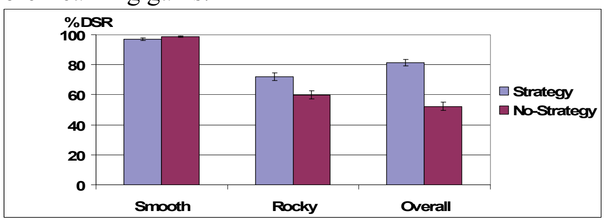

Figure 2: RSS_R on rocky, smooth and overall solutions

Strategy usage

Finally, we examined students’ strategies more closely. If a student applied the TVS, we would expect the order of the equations to follow the BC order since TVS is a BC problem-solving strategy. Thus, we subcategorize each desirable step into (1) FC, (2) BC, (3) combined equations (CB), or (4) Others. CB refers to equations that are algebraic combinations of several principle applications. For example: Tme=0.5*m*v^2+ m*g*h combines three principles: Tme=Ke+Gpe; Ke=0.5*m*v^2, and Gpe=m*g*h. We defined four ratios: BC%, FC%, CB% and Others%, by dividing each count by desirable steps, e.g. BC% is the proportion of desirable steps that were coded as BC.

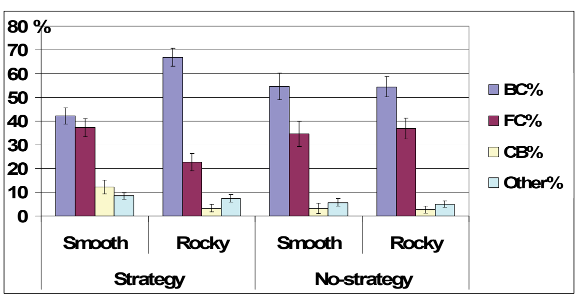

Figure 3: Strategy usage.

Figure 3 shows that the No-strategy students demonstrated very similar problem-solving strategies in the rocky and smooth solutions. The Strategy students, on the other hand, demonstrated different strategies. The data were analyzed using a mixed between-within repeated measures ANOVA with condition as the between subjects variable, and solution and strategy as two within-subjects variables. The analysis showed that the two conditions are significantly different overall: $F(1, 40)=8.102$, $p=0.007$. In addition, the pattern of strategy use was different for the two conditions, $F(3, 120) = 39.735$, $p < .0005$. Finally, there was a significant 3-way interaction involving condition, strategy, and solution, $F(3,20) = 2.712$, $p < 0.05$. Specifically, the Strategy students demonstrated a greater difference between BC and FC in rocky solutions than the smooth solutions, whereas there was no such difference in the no-strategy condition. No other effects were significant.

Discussion

Learning a problem solving strategy, the TVS, in one task domain, probability, noticeably improved students’ learning in a second domain, physics. Three analyses showed that Strategy students exceeded No-strategy students in their ability to solve physics training problems on their own. The Strategy students (1) asked for significantly less next-step help, (2) produced significantly more smooth solutions and fewer help-abuse solutions, and (3) had significantly higher desirable step ratio (DSR) overall. One interpretation of these results is that the TVS functioned as strategic resource that the Strategy students could use when they got stuck or began to doubt their progress. The No-strategy students lacked this resource, so they sought help from hints instead, often by asking for hints on every step (help-abuse).

Learning the TVS in probability also altered the distribution of strategies employed on non-help-abuse solutions to physics training problems. Regardless of whether the solution was smooth or rocky, the No-strategy students displayed the same distribution of strategies while the Strategy students displayed different ones. The Strategy students tended to use the BC strategy on rocky solutions, but shifted to FC or equation combining during the smooth solutions. One interpretation of the strategy-distribution findings, among many, is that the Strategy students were beginning to master the principles well enough that they could plan solutions in their heads, as experts do (Chi, Glaser & Rees, 1982; Priest & Lindsay, 1992), at least on easier problems. This allowed them to combine equations algebraically before writing them down or to write the equations in FC order. However, on harder problems, they continued to use the TVS because they could not plan far enough ahead.

This explanation, which is based on principle mastery, makes sense given the behaviors of the two tutoring systems. As part of the TVS, Pyrenees often asks the student “Which principle do you want to apply?” Only after a principle application has been specified are students allowed to enter an equation. In contrast, Andes allows students to enter equations without specifying principle applications. Therefore, the TVS strategy draws students’ attention to individual principles so they may have learned to think of problem-solving as application of individual principles. Moreover, by applying the TVS, the Strategy students may realize that the only hard subtask is to choose a proper principle—once that is done, writing the equation and solving it becomes routine. Therefore, the better they know the principles, the more successful they may become at this key subtask. This meta-cognitive realization may persist into the second task domain, physics. When they are given a sequence of single-principle physics problems, they would then pay more attention to the principles because they realize that they will need to know them well later. This could explain why the Strategy students outscored the No-strategy students on the physics single-principle problems of Table 3.

In contrast, the No-strategy students are simply asked to enter equations in Andes. They may have adopted an emphasis on memorizing them in lieu of other things. They may not see the equations as applications of principles, but as lines in the solution of a problem. They may focus on acquiring schemas that are the size of a whole problem (Sweller, 1988). Solving a new problem becomes a matter of piecing together equations from partially recalled problem schemas, which would explain why the equations are entered in a mixture of FC and BC orders, and the distribution of strategies is the same on both rocky and smooth solutions. This would also explains why No-strategy students ask for help more frequently and why they more often just give up on solving the problem and instead ask the tutor to solve it for them (help-abuse) so that they can see another worked example and (in their view) study another problem schema.

In short, our conjecture is that the most important element that transfers between probability and physics is not the TVS per se, but the meta-cognitive focus on principle applications vs. problem schemas. Nonetheless, it must also be said that the evidence for this conjecture is not sufficient. Our analysis of the log data is continuing.

To summarize, we have found that teaching students an explicit problem-solving strategy did not merely give the Strategy students a head start in learning physics, as one would expect from identical-elements theories of transfer (Singley & Anderson, 1989); instead, it increased the students' *rate* of learning of physics. Such acceleration of future learning is rarely found, which makes it a particularly intriguing form of robust learning. It may be related to Preparation for Learning and Adaptive Expertise (Schwartz & Bransford, 2005). Moreover, the large size of this cross-domain transfer (approximately 1 standard deviation effect size) suggests that it may have important applications in education. Taken literally, this lab experiment suggests that teaching students one course in a single deductive task (e.g., a discrete math) using Pyrenees may cause them to learn more quickly and deeply in subsequent courses, including physics and many others. The next step toward application should probably be an *in vivo* experiment in the PSLC physics LearnLab (www.learnlab.org).

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