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Fading from Worked Examples to Practice Problems: An Instructional Design Model

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Advanced Topics in e-Learning
Instructional Design

Fading from Worked Examples to Practice Problems: An Instructional Design Model

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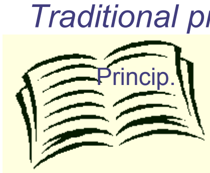
Learning from Worked-Out Examples: What Does it Mean?

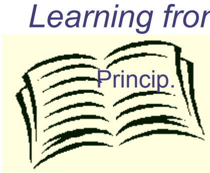
Early stage:	Intermediate stage:	Late stage:
Basic knowledge of principles	Understanding how to apply principles	Heightening speed and accuracy

Traditional procedure



Example | Problem | Problem | Problem | …

Learning from worked-out examples



Example | Example | … | Problem | Problem | …

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Significance of Worked-Out Examples

- In initial cognitive skill acquisition, worked-out examples ...
  - model how to apply domain principles;
  - are preferred by learners; and
  - are typically very effective (retention & transfer).

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Why is Learning from Worked-Out Examples Effective?

- Main goal in the intermediate stage: Understanding.
- Gaining understanding is fostered not primarily by solving problems and applying weak methods but by self-explanations.
- Self-explanations can hardly occur when cognitive capacity is "absorbed" by applying weak methods.
- Worked-out examples "free" cognitive capacity that can be devoted to self-explanation.
- Renkl et al. (2005) empirically validated this "cognitive load"-explanation by an experiment employing the dual-task paradigm.

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Moderating Factors

- Self-explanations
- Instructional explanations
- Intra-example features
- Inter-example features

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Moderating Factors: Self-Explanation Effect

Moderating factors:
- Self-explanations
- Instructional explanations
- Intra-example features
- Inter-example features

- Chi et al. (1989):
  - Self-explanation effect
- Renkl (1997):
  - Replication and extensions:
  - Two ways of effective learning:
  - Principle-based explainers (low prior knowledge)
  - Anticipative reasoners (high prior knowledge)

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Moderating Factors:
Inducing Self-Explanations

Moderating factors:
- Self-explanations
- Instructional explanations
- Intra-example features
- Inter-example features

- Renkl, Stark, Gruber, & Mandl (1998):
  - Effective short training that fostered self-explanations and learning outcomes
- Atkinson and Renkl (2005):
  - Prompts to identify underlying principles at worked-out steps + feedback fostered learning outcomes (2 experiments)

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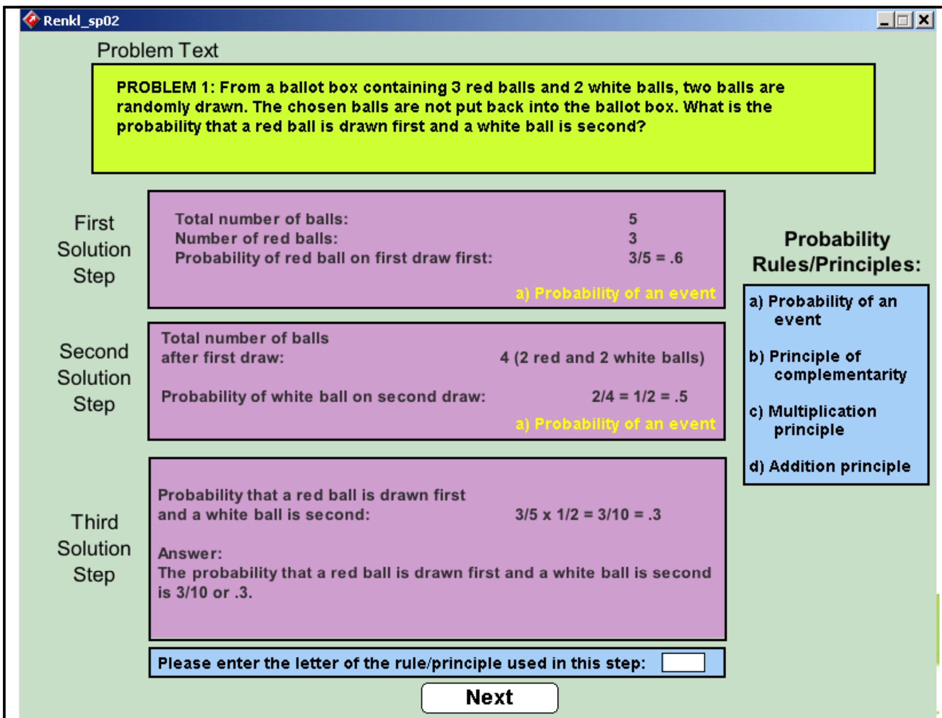

Moderating factors:
- Self-explanations
- Instructional explanations
- Intra-example features
- Inter-example features

Moderating Factor: Instructional Explanations

- Findings in general: Difficult to implement effective instructional explanations
- Atkinson & Renkl (2001) after some "iterations":
  - Instructional explanation based on a set of instructional principles (e.g., connected to anticipating, minimalist explanations, focus on principles) can foster learning

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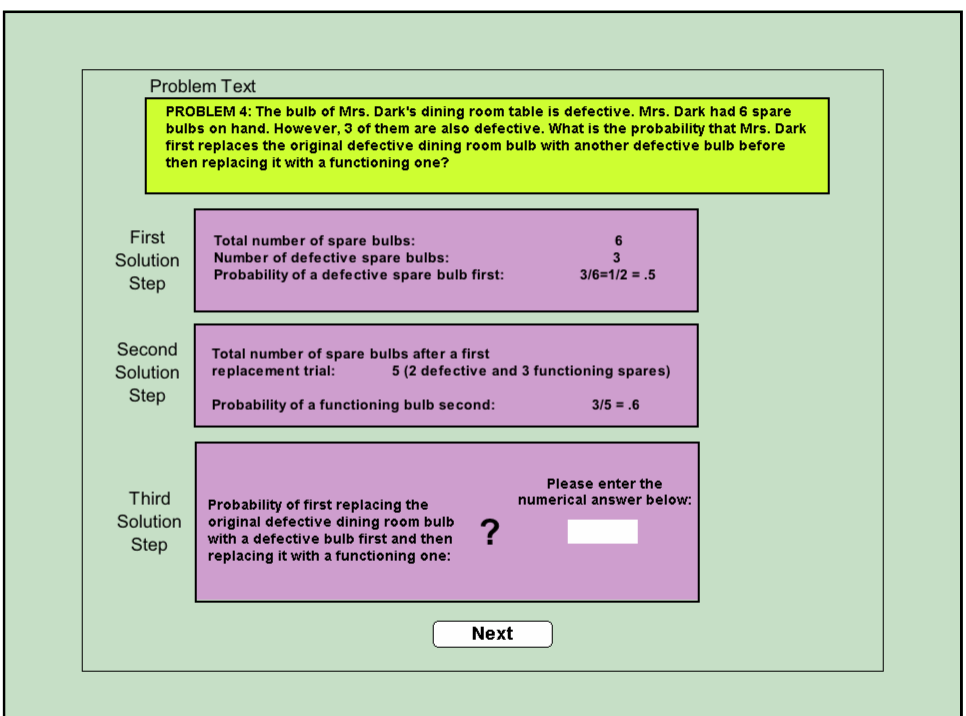

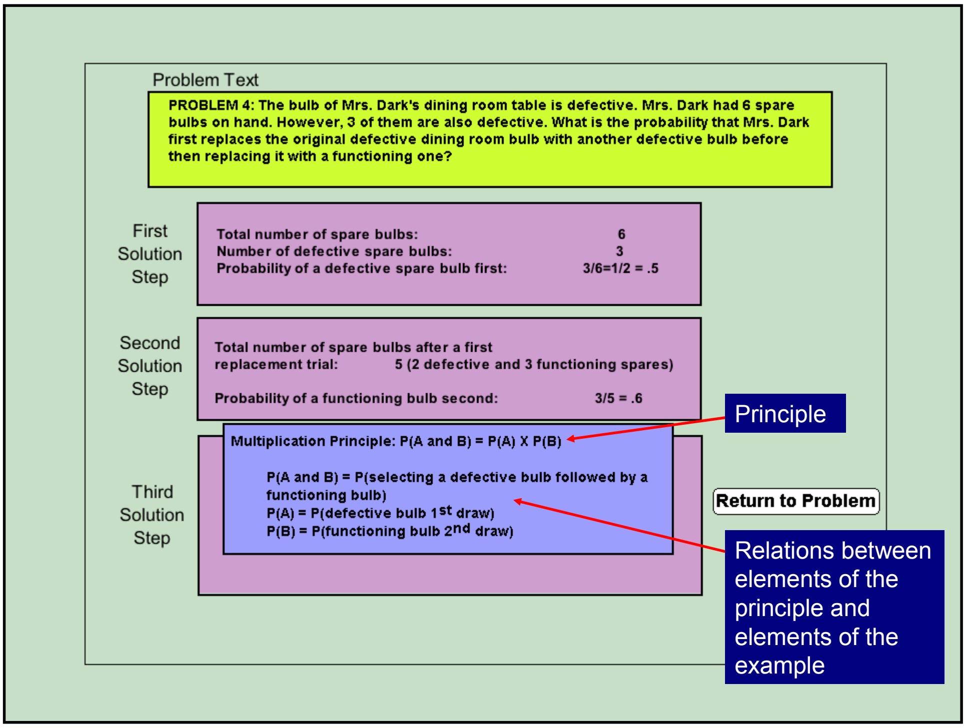

Moderating Factor:
Intra-Example Feature

Moderating factors:
- Self-explanations
- Instructional explanations
- Intra-example features
- Inter-example features

- Stark (1999)
  - Employment of incomplete examples after a set of complete examples → Induction of anticipation + Feedback
  - Self-explanations and learning outcomes were fostered.
  - Nevertheless: Self-explanations far from optimal → Instructional explanations?

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Problem Text

PROBLEM 4: The bulb of Mrs. Dark's dining room table is defective. Mrs. Dark had 6 spare bulbs on hand. However, 3 of them are also defective. What is the probability that Mrs. Dark first replaces the original defective dining room bulb with another defective bulb before then replacing it with a functioning one?

First Solution Step

Total number of spare bulbs:	**6**
Number of defective spare bulbs:	**3**
Probability of a defective spare bulb first:	**3/6=1/2 = .5**

Second Solution Step

Total number of spare bulbs after a first replacement trial:	**5 (2 defective and 3 functioning spares)**
Probability of a functioning bulb second:	**3/5 = .6**

Third Solution Step

Probability of first replacing the original defective dining room bulb with a defective bulb first and then replacing it with a functioning one: **?**

Please enter the numerical answer below:

Next

Moderating Factor:
Inter-Example Features

Moderating factors:
- Self-explanations
- Instructional explanations
- Intra-example features
- Inter-example features

Fading worked-out steps in a sequence of isomorphic examples/problems (Atkinson & Renkl (2005); Renkl, Atkinson, Maier, & Staley, 2002)

Early stage:	**Intermediate stage:**	**Late stage:**
Basic knowledge of principles	Understanding how to apply principles	Heightening speed and accuracy

Example | Inc. Ex | Inc | Problem | …

Fading fostered near (and far) transfer (4 experiments)

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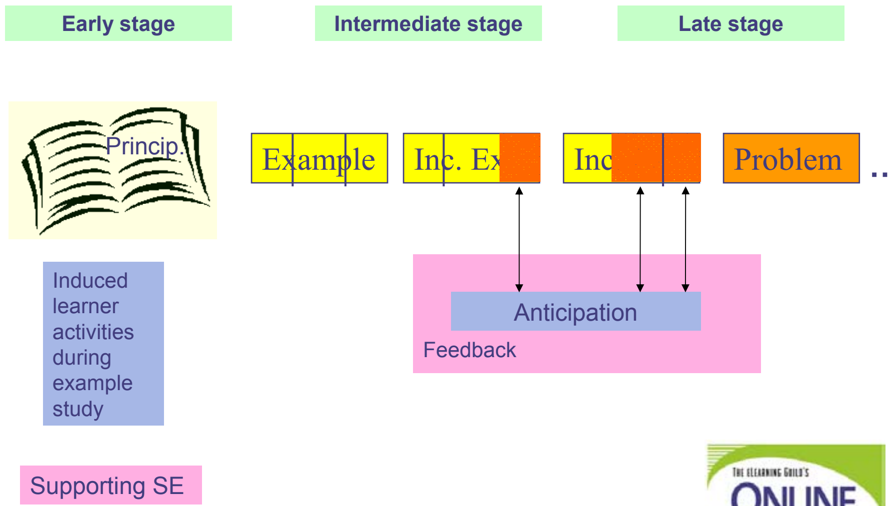
Fading from Worked Examples to Practice Problems: An Instructional Design Model



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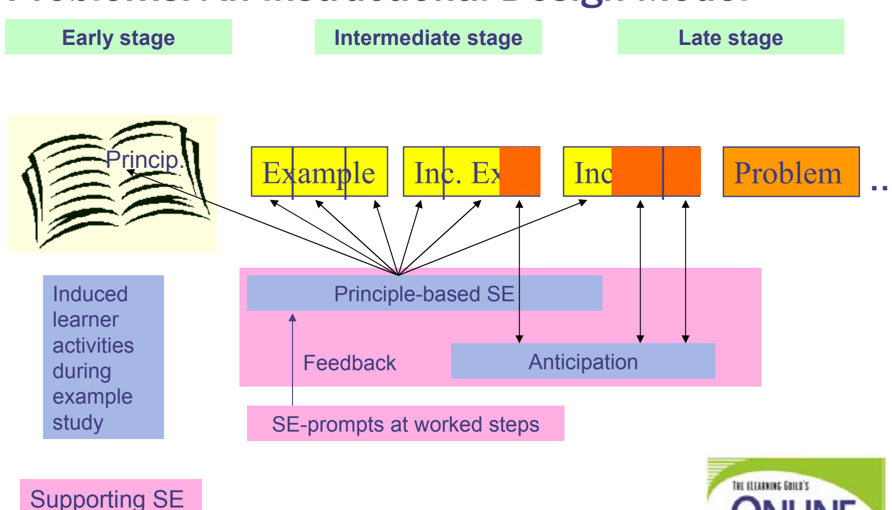
Fading from Worked Examples to Practice Problems: An Instructional Design Model



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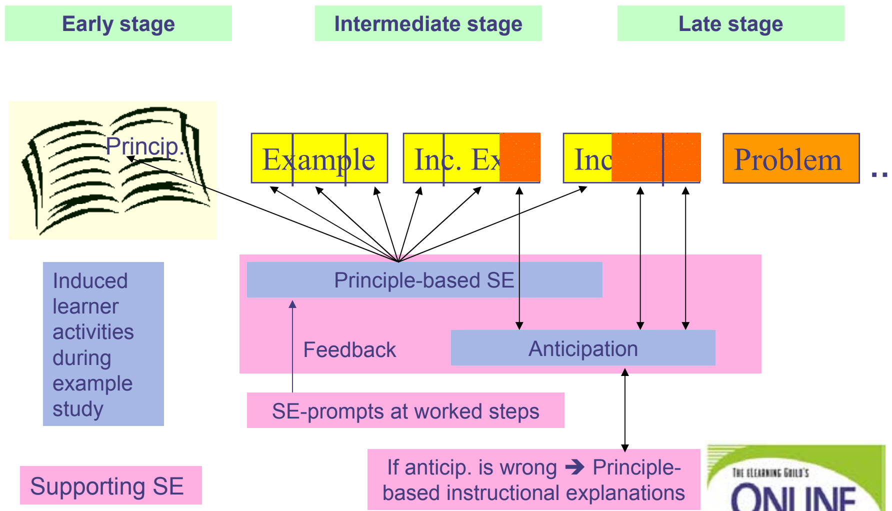
Fading from Worked Examples to Practice Problems: An Instructional Design Model



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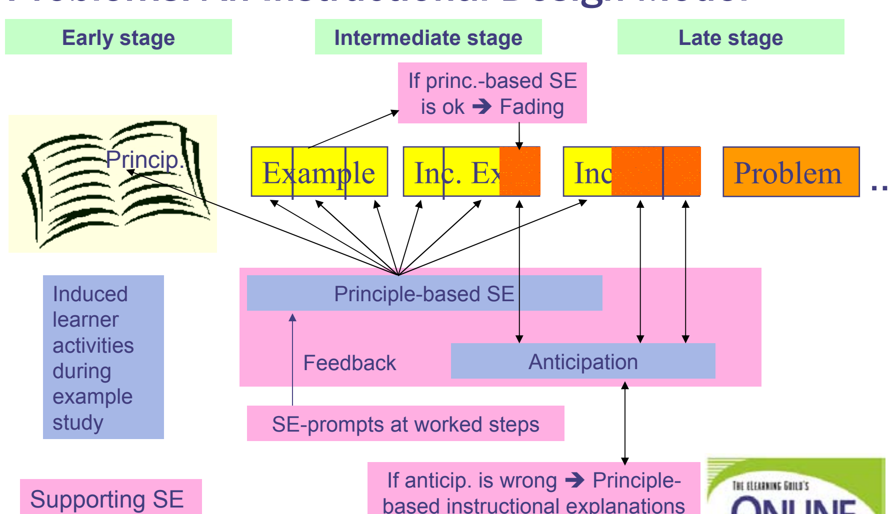
Fading from Worked Examples to Practice Problems: An Instructional Design Model



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Essential Elements of the Instructional Sequencing Model

1. Sequence of isomorphic examples/problems
2. Prompts for principle-based explanations at worked-out step
3. Feedback on principle-based explanations
4. Fading worked-out steps → anticipations
5. Feedback about anticipations
6. In the case of wrong anticipations → principle-based instructional explanations
7. Fading steered by indicators of prior knowledge about certain types of steps

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Transitioning From Studying Examples to Solving Problems: Effects of Self-Explanation Prompts and Fading Worked-Out Steps

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Although research has demonstrated that successively fading or successively removing more and more worked-out solution steps as learners transition from relying on examples to independent problem solving reliably fosters performance on near-transfer tasks—relative to example–problem pairs—this effect is not reliable on far-transfer tasks. To address this, the authors combined fading with the introduction of prompts designed to encourage learners to identify the underlying principle illustrated in each worked-out solution step. Across 2 experiments, this combination produced medium to large effects on near and far transfer without requiring additional time on task. Thus, the instructional procedure is highly recommendable because it (a) is relatively straightforward to implement, (b) does not prolong learning time, and (c) fosters both near- and far-transfer performance.

Worked-out examples typically consist of a problem formulation, solution steps, and the final answer itself. Research indicates that exposure to worked-out examples is critical when learners are in the initial stages of learning a new cognitive skill in well-structured domains such as mathematics, physics, and computer programming (Anderson, Fincham, & Douglass, 1997). Moreover, studies performed by Sweller and his colleagues (e.g., Sweller & Cooper, 1985; for an overview, see Sweller, van Merriënboer, & Paas, 1998) document that learning from worked-out examples can be more effective than learning by problem solving.

Although worked-out examples have significant advantages, their use as a learning methodology does not, of course, guarantee effective learning. Chi and her colleagues (Chi, Bassok, Lewis, Reimann, & Glaser, 1989) noted that examples drawn from college-level physics textbooks often do not include all of the reasons why a certain step in the solution was performed. As a result, the burden of explaining the solution steps rests on the learner. Chi et al. (1989) discovered that learners attempted to establish a rationale for the solution steps by pausing to explain the examples to themselves and that these learners appeared to learn more than those who did not—a phenomenon they termed the *self-explanation effect*.

Self-Explanation Effect

At first, Chi and her colleagues (Chi et al., 1989) postulated that the self-explanation effect principally involved inference generation on the part of a learner. That is, by self-explaining, the learner is inferring information that is missing from a text passage or an example's solution. However, because of some inconsistencies among this view and some of the findings in the self-explanation literature, Chi (2000) revised this initial view by suggesting that the self-explanation effect is actually a dual process, one that involves generating inferences and repairing the learner's own mental model. In the latter process, it is assumed that the learner engages in the self-explanation process if he or she perceives a divergence between his or her own mental representation and the model conveyed by the text passage or example's solution. According to Chi, this new viewpoint extends the inference generation by suggesting that "each student may hold a naive model that may be unique in some ways, so that each student is really customizing his or her self-explanations to his or her own mental model" (p. 196).

According to Renkl (1997), there are four relatively distinct self-explanation styles, two associated with successful problem-solving strategies and two associated with inadequate strategies. Although he found that most learners were actually passive or superficial explainers who did not appear to learn much, Renkl (1997) discovered that the successful learners could be classified as either anticipative reasoners or principle-based explainers. He classified learners who tended to self-explain by anticipating the next step in an example solution, then checking to determine whether the predicted step corresponded to the actual step as

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We thank Paige Patterson for her assistance in running participants and coding data in Experiments 1 and 2. A subset of the results from Experiment 1 was reported at the American Educational Research Association, New Orleans, Louisiana, April 2002.

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anticipative reasoners and noted that these learners started the learning process with a relatively high level of prior knowledge. Principle-based explainers, on the other hand, tended to identify the essential meaning of a problem by attempting to articulate its goal structure—including the application of operators—while also elaborating on the principle that the example was intended to convey. In contrast to the anticipative reasoners, however, these principle-based explainers had low prior knowledge. Thus, these findings suggest that it is functional to elicit principle-based explanations to learners with low prior knowledge while encouraging anticipative reasoning to learners with high prior knowledge.

Besides findings from correlational studies such as the ones by Chi et al. (1989) and by Renkl (1997), there is also experimental evidence that corroborates the significance of self-explanations when studying examples. In a study conducted by Renkl, Stark, Gruber, and Mandl (1998), learners in an experimental group were informed about the importance of self-explanations before being presented with a live model depicting how to self-explain. The control group, on the other hand, received think-aloud training instead of self-explanation training before the presentation of the instructional examples. According to their results, a short self-explanation training procedure produced an increase in the frequency of self-explanation activities among the learners in the experimental condition and enhanced both near-transfer performance (i.e., problems with the same structure or solution rationale but different surface features such as objects and numbers) and far-transfer performance (i.e., problems with different structure that required the generation of a modified solution procedure).

Similarly, Conati and VanLehn (1999, 2000) created and evaluated a computer-based learning environment designed to support learning from worked-out examples by prompting self-explanations. A tutorial component contained templates that were to be filled in by browser items (physics rules or subgoals in a solution plan) as building blocks of self-explanations. In addition, the tutorial component gave hints as to which aspects needed further self-explanations. Contrary to expectation, however, this environment did not foster learning gains—with the exception of some subgroups that were identified post hoc as profiting from the tool. Similarly, Hausmann and Chi (2002, Experiment 1) did not find positive effects of a computer-based facility where the students were encouraged to contribute their own written self-explanations by typing them into the computer. On the other hand, Aleven and Koedinger (2002) obtained positive results with prompting for self-explanations during problem solving rather than during example study in an intelligent instructional environment. Specifically, they documented that problem-solving practice within such a learning environment can be enhanced with prompting the learners to self-explain by identifying the underlying problem-solving principles. In summary, the findings concerning the use of self-explanation prompting in a computer-based learning environment are mixed and need further investigation.

Fading From Example Study to Problem Solving

It is also important how the instructional materials (examples and problems) are designed (for an overview, see Atkinson, Derry, Renkl, & Wortham, 2000). For instance, pairing examples with practice problems is more effective than exposing learners to either sets of examples only (Trafton & Reiser, 1993) or practice problems only (Sweller & Cooper, 1985). Recently, Renkl, Atkinson, and Maier (2000) proposed a variation of the traditional method of pairing examples with practice problems. They tested whether the two learning modes (i.e., example study and problem solving) could be combined by successively introducing more and more elements of problem solving in example study until learners are solving the problems on their own. In this way, more and more elements of anticipation are introduced when the knowledge level of the learner increases.

According to Renkl et al. (2000), this rationale is useful as a way to structure the transition from studying examples in initial skill acquisition to problem solving in later phases of the learning process. Specifically, they combined problem solving and example study in the following way. First, a complete example was presented (model). Second, an example was given in which one single solution step was omitted (scaffolded problem solving). Then, the number of blanks was increased step by step until just the problem formulation was left, that is, a problem to be solved (independent problem solving). In this way, a smooth transition from modelling (complete example) to scaffolded problem solving (incomplete example) to independent problem solving was implemented.

As a first step for testing this fading procedure, Renkl and his colleagues (Renkl, Atkinson, Maier, & Staley, 2002) explored the effectiveness of fading from example study to problem solving against the traditional method of using example–problem (EP) pairs within a computer-based environment. Across a field experiment and two controlled laboratory experiments, Renkl et al. (2002) found that (a) their fading procedure produced reliable effects on near-transfer items but not on far-transfer items, (b) the number of problem-solving errors generated during the learning phase played a role in mediating the effectiveness of the fading procedure, and (c) it was more advantageous to fade out worked-out solution steps using a backward approach by omitting the last solution steps first instead of omitting the initial solution steps first (i.e., a forward approach).

Because the fading procedure did not produce reliable effects on far transfer, this raises the question as to whether there are other instructional approaches that can be combined with fading from example study to problem solving that can foster far transfer in particular. For instance, although the fading procedure encouraged the learners to generate anticipations on those steps where the solutions were omitted, during the study of worked-out steps there was no instructional means to induce active processing. This might be a major drawback of this learning environment, especially because Renkl (1997) has shown that most learners are passive or superficial self-explainers. On the other hand, a learning environment that combines the procedure with prompts to encourage more active example processing during the study of worked-out steps—for instance, prompts that elicit principle-based self-explanations—might foster far transfer better than fading alone. By combining prompting at worked-out steps with fading (i.e., inducing anticipation), the learners would be required to learn in a fashion considered more favorable according to the findings of Renkl (1997), that is, to elicit principle-based self-explanations in the initial stages of learning and followed by a procedure that induces anticipations.

Overview of Experiments

On the basis of the aforementioned research, it appeared worthwhile to examine whether a learning environment that relies on fading could also incorporate explicit self-explanation prompts to encourage learners to think more deeply about the structure of the worked-out steps, thereby improving subsequent performance on far-transfer problems drawn from well-structured domains. The purpose of the present research was to examine the impact of two instructional approaches—backward fading (BF) and EP pairs—in combination with the presence or absence of self-explanation prompts on transfer across a set of probability tasks. Specifically, the aim of Experiment 1—a laboratory-based experiment—was to examine whether there was a positive learning effect associated with fading and/or self-explanation prompts—straightforward prompts designed to permit the learner to tailor his or her self-explanation according to his or her own mental model of the situation at hand—and whether there was an interaction between the use of fading and the use of self-explanation prompts. Although prior to the experiment we hypothesized that learners assigned to a BF condition would produce significantly more accurate near-transfer solutions than their counterparts assigned to the EP-pairs condition, the impact of self-explanation prompts and the interaction between prompts and type of instruction remained open questions. The goal of Experiment 2 was to replicate the novel findings of Experiment 1 within a more authentic, school-based setting. Across the two experiments, a common set of learning-process and learning-outcome measures were collected. The learning-process measures included accuracy of anticipations during learning and study time. In addition, Experiment 1 included the correctness of the learners' responses to the self-explanation prompts. The learning-outcome measures included correctness of solutions on near-transfer problems and far-transfer problems.

Experiment 1

This experiment was designed to address three research questions: (a) Does the BF produce more favorable learning outcomes than EP pairs? (b) Does the use of self-explanation prompts in comparison with the lack of such prompts lead to better learning outcomes? (c) Is there an interaction between the use of fading (vs. EP pairs) and the use of self-explanation prompts (vs. no prompts)?

Method

Participants and design. The participants of this study were 78 educational psychology and psychology students (27 freshmen, 27 sophomores, 13 juniors, and 11 seniors) at a large, southeastern university. The sample comprised 15 males and 63 females (mean GPA $= 3.07$, mean ACT score $= 21.99$). The participants were randomly assigned in approximately equal proportions to the cells of a 2×2 between-subjects factorial design. The first factor was the characteristics of the instructional material (BF or EP pairs). The second was the presence or absence of self-explanation prompts. Thus, this experiment consisted of four conditions: (a) BF only ($n = 19$), (b) EP pairs only ($n = 19$), (c) BF plus prompting ($n = 20$), and (d) EP pairs plus prompting ($n = 20$).

Pencil–paper materials. The pencil–paper materials included a demographic questionnaire, an overview of the fundamental principles of probability, a nine-item pretest, and a 13-item posttest. The questionnaire asked each learner to provide demographic information (e.g., standardized test scores, number of postsecondary statistics courses in progress or completed) that could be used to judge the learner's prior knowledge in statistics and mathematics in general. The five-page overview of the fundamental principles of probability covered such topics as (a) experiment and sample space, (b) probability of an event, (c) probability of the nonoccurrence of an event (i.e., the principle of complementarity), (d) probability of the linked occurrence of events (i.e., the multiplication principle for independent events), and (e) probability of A and/or B (i.e., the addition principle). The following is an excerpt from the overview's treatment of the topic of experiment and sample space:

> When doing an experiment, different events can occur; for example, a specific ball is pulled out of the ballot box or a specific number appears on a die. The sum of all possible events that can occur during an experiment is referred to as the *sample space*. For instance, if a six-sided die is rolled, the sample space includes the six numbers that can possibly appear on the die. On the other hand, if a coin is flipped, the sample space includes the two events that can occur, "heads" and "tails."

The pretest was designed to assess prior knowledge, and it consisted of nine relatively straightforward probability calculation problems (e.g., "When rolling a six-sided die what is the probability that 2 or 4 will appear?"). The posttest consisted of 13 problems including one very simple warm-up problem, which was ignored in our final analysis. Unlike the pretest, where each item only required the application of one probability principle per item, the 12 posttest items used in the final analysis each involved the coordinated application of several probability principles. Furthermore, the 12 posttest problems consisted of six near-transfer items and six far-transfer items. The near-transfer problems had exactly the same underlying structure (i.e., solutions involved the same set of probability principles applied in exactly the same manner) as several of the examples−problems the learners encountered during the learning phase but differed only in terms of surface characteristics (i.e., cover story, values for the problem parameters). Thus, despite sharing the same solution rationale, the near-transfer items and their structurally similar examples−problems from the learning phase appear different on the surface because they did not share either cover stories or problem values. The following is an example of a near-transfer item that is structurally isomorphic to several of the examples−problems provided during the learning phase:

> Charley needs an egg for cooking but is aware that some of the dozen eggs in his fridge are rather old and probably spoiled. Although he is not aware of it, four eggs are still edible while eight eggs are spoiled. He does know, however, that spoiled eggs unlike fresh eggs float in water. What is the probability that if Charley puts two eggs into the water that the first one floats but the second egg sinks?

On the other hand, far-transfer problems differed from the examples–problems provided during the learning phase with respect to both structure and surface features. That is, the far-transfer problems not only differed from the examples–problems from the learning phase in terms of their cover stories and values for the problem parameters, but also in terms of their solution rationale (i.e., solutions involved the same or similar sets of probability principles applied in different combinations). Thus, for the learner to correctly solve any of the far-transfer problems, he or she had to modify the problem-solving procedures illustrated in items from the learning phase to derive a solution to the novel transfer problems. The following is an example of a far-transfer item:

> When driving to work, Mrs. Fast has to pass the same traffic light twice—once in the morning and once in the evening. It is green in 70% of the cases. What is the probability that she can pass through a green light in the morning but has to stop in the evening?

Computer-based learning environment. Director 6.0 (Macromedia, 1997) software, an authoring tool for multimedia productions, was used to create the Windows-based learning environment used in this experiment. The learning environment was originally developed by Renkl (1997), modified by Stark (1999), and finally adapted to the present needs by Robert K. Atkinson. This computer-based learning environment was designed to deliver instruction to learners learning to solve probability word problems. It consisted of a set of worked-out examples and problems from the domain of probability calculation. On the whole, the instructional lesson consisted of two sets of probability tasks where each set consisted of four tasks with the same underlying structure (i.e., solution rationale) but different surface features (i.e., cover stories, values). Across all four tasks, the worked-out examples and problems consisted of exactly three solution steps or subgoals. To assist the learner in distinguishing a problem's subgoals, we visually isolated and labeled each of the three subgoals (e.g., *first solution step*). The following is the cover story from one of the worked examples provided during the learning phase:

> Mrs. Zinfandel purchased 12 bottles of her favorite vintage red wine. Unfortunately, due to improper storage, 4 bottles have turned to vinegar and are undrinkable. What is the probability that the first bottle that Mrs. Zinfandel opens is vinegar but the second one is drinkable?

The learning environment was configurable to run in one of four modes that reflected the four conditions of the present experiment. First, in the BF-only condition, the first task in each of the two sets was a completely worked-out example where all three of the problem's solution steps were sequentially provided to the learner. That is, instead of appearing on the screen as a completely worked-out example, this task appeared at the outset unsolved. The learner moved forward through the example by clicking on a *next* button and watched as each of the three solution steps was successively added—like a learner-paced animation—over a series of pages, with the final page containing the entire solution. Once the learner finished inspecting this worked example, he or she then proceeded to the next page by clicking on a button marked *next problem* located at the bottom of the page. The second task was similar to the first, with one notable exception: The final (i.e., third) solution step was omitted (see Table 1). Instead of presenting this step, the learner was required to anticipate this step on his or her own by typing in the solution into a field located on the screen (see Figure 1), otherwise he or she could not continue. The learning environment was programmed to record the correctness of the problem-solving attempts in a log file for subsequent analysis. After inputting the anticipated answer, the learner clicked the *next* button at which time the correct solution step was displayed for the learner to receive feedback on the correctness of his or her problem-solving attempt (see Figure 2). In the third task of each set, the first solution step was provided and the last two steps were omitted. As with the previous task, the learner was required to input a solution before continuing. Finally, in the fourth task of each set, all three steps were omitted. Thus, the final task of each set was essentially a problem-solving task.

In the EP-only condition, each set comprised two pairs of a completely worked-out example followed by a problem-solving task. In other words, all three solution steps for the first and third tasks of each set were provided, whereas all three solution steps for the second and fourth tasks of each step were omitted. Across the two sets of problems, there were a total of 12 omitted steps—the same number of unsolved solution steps as found in the BF condition—where the leaner was required to anticipate the answers.

The BF-plus-prompting and EP-plus-prompting conditions were indistinguishable from the BF-only and EP-only conditions, respectively, with one notable exception: the presence of self-explanation prompts (see Figure 3). In the two prompting conditions, the learner was encouraged to self-explain each solved solution step by first examining the step and then identifying which principle of probability the step exemplified. To encourage this process, we prompted the learner to select the probability principle—the same principles covered in the introductory material covered in the handout (i.e., probability of an event, the principle of complementarity, the multiplication principle for independent events, or the addition principle)—from a list that appeared to the right of the solved solution step and enter his or her selection before being permitted to continue. Once a principle was selected, the learner's response plus the correct principle appeared below the solved solution step for the learner to scrutinize and check his or her accuracy.

Table 1
Description of Instructional Material

Tasks	Solution step	Condition: Backward fading	Condition: Example–problem pairs
1 and 5	1	Worked[a]	Worked
	2	Worked	Worked
	3	Worked	Worked
2 and 6	1	Worked	Omitted[b]
	2	Worked	Omitted
	3	Omitted	Omitted
3 and 7	1	Worked	Worked
	2	Omitted	Worked
	3	Omitted	Worked
4 and 8	1	Omitted	Omitted
	2	Omitted	Omitted
	3	Omitted	Omitted

Note. Tasks 1–4 were in Set 1, and Tasks 5–8 were in Set 2.
[a] The solution step was provided for the learner. [b] The learner was responsible for solving that particular solution step.

Scoring. Five measures required scoring: correctness of principles, accuracy of anticipations, pretest, near transfer, and far transfer. The learning environment automatically coded the learner's correctness of principles and accuracy of anticipations. In the two prompting conditions, the number of principles that the learners were required to identify was held constant at 12 across both types of instructional material. For each principle that the learners correctly identified, 1 point was awarded (no partial credit), thereby producing a maximum score of 12 for this measure. To create a proportion correct on the measure, we summed the participant's response and divided by 12. With regard to accuracy of anticipations, across all four conditions, the number of unsolved solution steps or anticipations was held constant at 12. For each solution step that the learners correctly anticipated the answer, 1 point was awarded (no partial credit), thereby producing a maximum score of 12 for this measure. The participant's response on this measure was summed and divided by 12, thereby generating a proportion correct on the measure, with values ranging from 0 to 1.

On the pretest, each correct solution was awarded 1 point (no partial credit), thereby generating a maximum score of 9 for the pretest. On the posttest, each problem consisted of three distinct solution steps. For each correct step, 1 point was awarded (partial correct). Thus, if the participants solved each solution step correctly, the problem solution was awarded 3 points. For both the near- and far-transfer measures, 18 was the maximum score that a learner could achieve (e.g., 3 points per problem times 6 near-transfer problems). To create a proportion correct score, with values ranging from 0 to 1, we summed the participants' responses on each measure (i.e., near and far transfer) across all six questions and divided by 18.

Procedure. Small groups of participants, varying in size from 1 to 10, were brought into a laboratory equipped with 10 Windows-based desktop computers (600 mHz, 256 RAM, 15-in. monitors), each located in their own cubicle. The participants were seated at the individual desktops and instructed to work independently of their peers. During

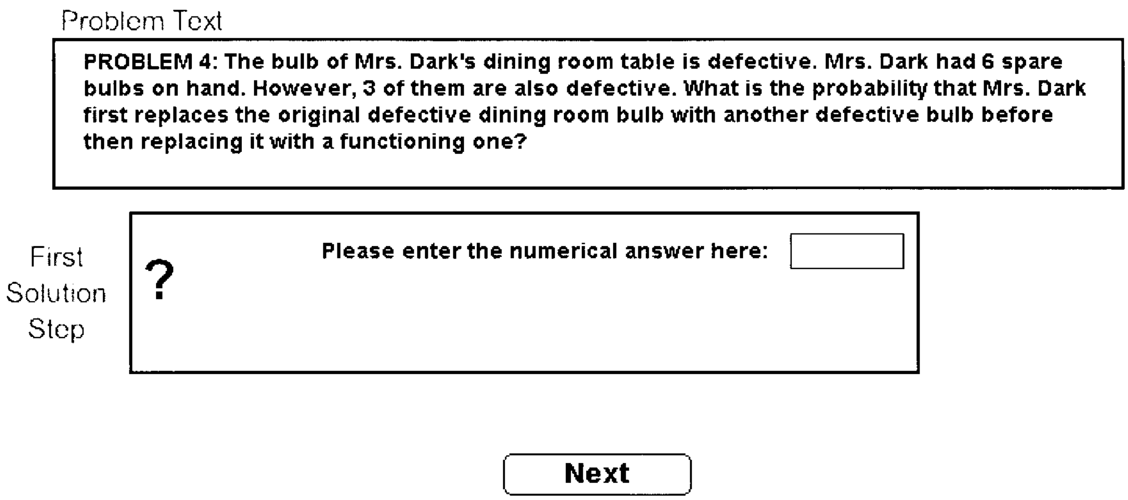

Figure 1. Example with a first missing solution step.

the course of the experiment, they spent approximately 90 min in the laboratory during which time they completed several tasks. First, the participants were asked to fill out a demographic questionnaire. Next, a pretest on prior knowledge in probability calculation was presented. To provide or reactivate basic knowledge that allowed the participants to understand the worked-out examples, we gave the participants an instructional text on basic principles of probability calculation. After reading this instructional text, the participants were to turn their attention to the computer-based learning environment and study the worked-out examples and solve the practice problems provided by the program. The participants were permitted to refer to the instructional text at any point during the computer-based portion of the experiment. During this phase, the experimental variation took place (BF vs. EP pairs, prompting vs. no prompting). The time spent for learning was recorded. Finally, the participants completed a posttest.

Results

Table 2 presents the mean scores and standard deviations for each group on each of the dependent measures. For the dependent measures, a 2 $\times$ 2 analysis of covariance (ANCOVA) was conducted using the pretest as a covariate (α = .05; exception: instructional time; see below). Each measure was tested for homogeneity of regression, and the results were found to be nonsignificant—all Fs $<$ 1.

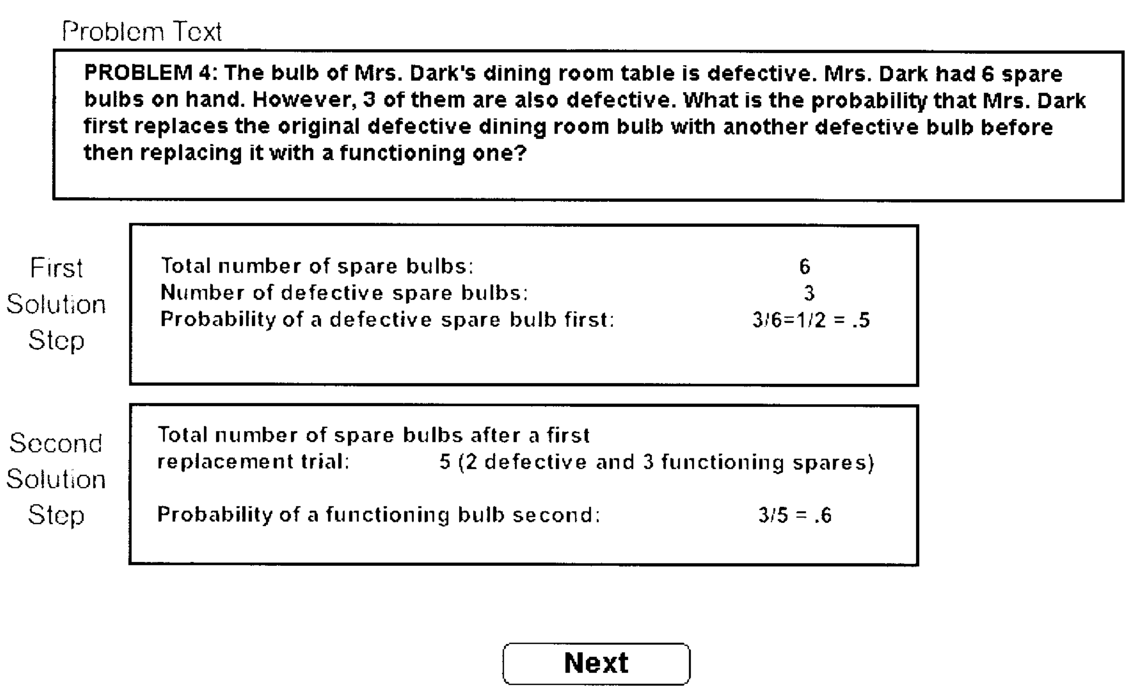

Figure 2. Example with a worked-out second solution step.

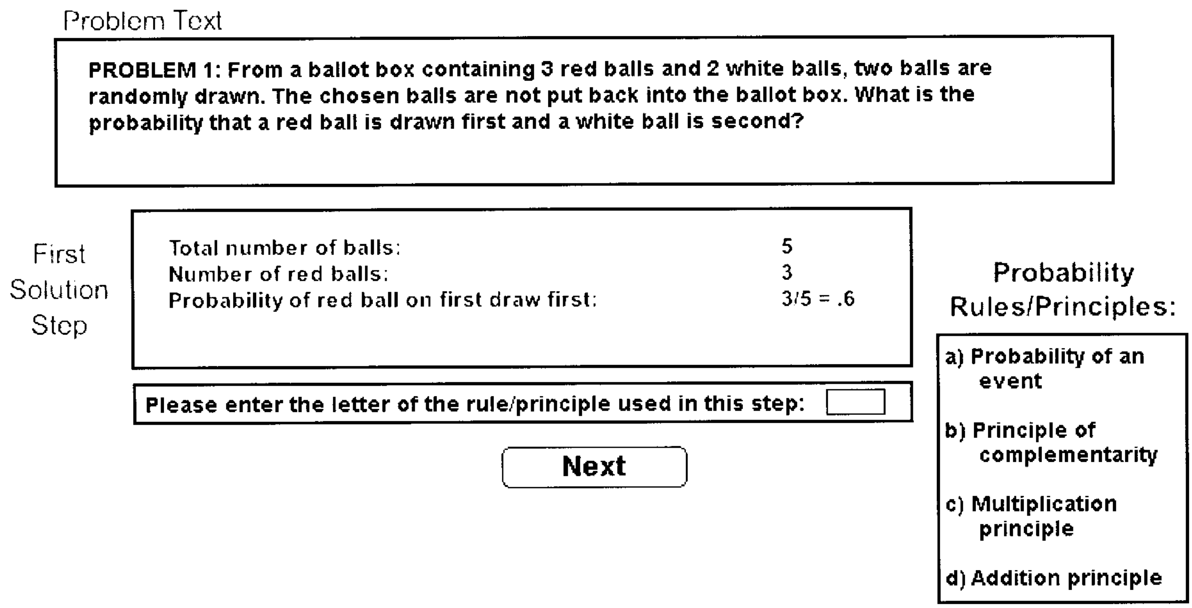

Figure 3. Example with a self-explanation prompt on the first solution step.

Analysis of learning-process measures. An ANCOVA revealed a significant main effect on anticipation for type of instruction, $F(1, 73) = 10.05$, $MSE = 0.07$, $p < .05$. The participants assigned to the BF conditions outperformed their peers in the EP-pairs conditions in terms of accuracy of anticipations. Cohen's f statistic for these data yields an effect size estimate of .33 for accuracy of anticipations, which corresponds to a medium to large effect. There was no significant main effect for prompting, $F(1, 73) = 0.66$, $p = .42$. There was also no interaction between type of instruction and self-explanation prompting, $F(1, 73) = 1.18$, $p = .28$.

To test for the possibility that the advantage of the prompting group could be attributed to time interacting with the instructional material, we conducted an analysis of variance (ANOVA) on instructional time. There was no significant main effect for prompting, $F(1, 74) = 0.01$, $MSE = 77.88$, $p = .95$, or fading, $F(1, 74) = 0.65$, $p = .42$. In addition, there was no significant interaction between these two factors, $F(1, 74) = 0.01$, $p = .94$. For correctness of principles, which only applied to the two prompting conditions (i.e., BF plus prompting and EP plus prompting), an ANCOVA yielded no significant main effect for accuracy of principles, $F(1, 36) = 0.19$, $MSE = 0.03$, $p = .66$.

Analysis of learning-outcome measures. There was a significant main effect for type of instruction material on near transfer, $F(1, 73) = 4.50$, $MSE = 0.05$, $p < .05$, where the participants who were assigned to the BF conditions significantly outperformed their counterparts in the EP conditions. Cohen's f statistic for these data yields an effect size estimate of .23 for near transfer, which corresponds to a medium effect. There was also a significant main effect for self-explanation prompting, $F(1, 73) = 5.01$, $p < .05$, where the participants who were presented with self-explanation prompts outperformed their peers who did not receive the prompts on near transfer. Cohen's f statistic for these data yields an effect size estimate of .25 for near transfer, which corresponds to a

Table 2
Study Time and Scores on Each Measure as a Function of Type of Instructional Material (Experiment 1)

	Example–problem pairs						Backward fading					
	No prompting ($N = 19$)			Prompting ($N = 20$)			No prompting ($N = 19$)			Prompting ($N = 20$)		
Measure	M	SD	Adj. M	M	SD	Adj. M	M	SD	Adj. M	M	SD	Adj. M
Pretest	4.21	2.02		5.35	1.81		4.95	1.76		5.58	2.32	
Correctness of principles				0.82	0.18	0.82				0.85	0.17	0.85
Accuracy of anticipations	0.42	0.29	0.48	0.52	0.30	0.49	0.73[a]	0.30	0.74	0.66[a]	0.33	0.62
Study time	33.05	2.03		31.30	1.97		33.05	1.97		31.58	2.03	
Near transfer	0.39	0.24	0.43	0.61	0.23	0.59[b]	0.58	0.25	0.58[a]	0.69	0.24	0.65[a,b]
Far transfer	0.36	0.18	0.40	0.52	0.20	0.50[b]	0.51	0.19	0.51[a]	0.60	0.18	0.57[a,b]

Note. Adj. = adjusted.
[a] Differs statistically from the example–problem pairs means. [b] Differs statistically from the no-prompting means.

medium effect. There was, however, no evidence of an interaction between the type of instructional material and the presence or absence of self-explanation prompts on this measure, $F(1, 73) = 0.81$, $p = .37$.

The same pattern of effects was evident on the far-transfer measure. As with near transfer, there was a significant main effect for type of instructional material, $F(1, 73) = 5.99$, $MSE = 0.03$, $p < .05$, where the participants in the BF conditions solved significantly more far-transfer problems than their peers assigned to the EP conditions. Cohen's f statistic for these data yields an effect size estimate of .27 for near transfer, which corresponds to a medium effect. Again, there was also a significant main effect for self-explanation prompting, $F(1, 73) = 4.50$, $p < .05$, where the participants who received self-explanation prompts produced significantly more accurate solutions to the far-transfer problems in comparison with their counterparts who did not receive the prompts. Cohen's f statistic for these data yields an effect size estimate of .23 for near transfer, which corresponds to a medium effect. There was, however, no evidence of an interaction between the type of instruction and the presence or absence of self-explanation prompts on this measure, $F(1, 73) = 0.31$, $p = .58$.

Discussion

Is there a positive learning effect associated with fading? The results of this experiment essentially replicate the findings of Renkl et al. (2002). That is, the BF condition was associated with a higher solution rate of near-transfer problems as Renkl et al. (2002) documented in Experiments 1, 2, and 3. Moreover, we provide additional support for the notion that the BF condition produced more accurate solutions on far-transfer problems, an effect that was inconsistent across the experiments in Renkl et al.'s (2002) study. Thus, it appears that the BF procedure can substantially foster both near and far transfer. In addition, the BF procedure resulted in a statistically significant effect on accuracy of anticipations. Finally, the advantage of fading could not be attributed to additional time on task.

Do self-explanation prompts impact learning? In contrast to the results of Conati and VanLehn (2000)—but in accord with Aleven and Koedinger's (2002) findings—a simple prompting procedure can substantially foster both near and far transfer. Hence, the acquisition not only of (relatively simple) rules (i.e., near transfer) but also of understanding (i.e., far transfer) can be fostered by this instructional procedure. It is also notable that the advantage of prompting could be achieved without significantly increasing learning time. This is a particularly important accomplishment in light of the fact that this prompting procedure—one that proved to be both effective and efficient—is a very simple and easy-to-implement feature for computer-based learning environments.

Is there an interaction between the use of fading and the use of self-explanation prompts? According to the results of this experiment, there was no evidence of an interaction between the use of fading and the use of self-explanation prompts on any of the measures. This may be regarded as a positive finding from an educational point of view because both instructional means produced at least medium effects on learning outcomes and were combined without causing any decrement in performance.

In sum, although there is little doubt after this experiment that near and far transfer is fostered by the BF procedure—an effect that has been consistently found across several studies—the effect of prompting, albeit positive, remains in contrast less substantiated. The results of Conati and VanLehn (2000) as well as of Hausmann and Chi (2002) in particular indicate that these results should be interpreted cautiously until they can be replicated. Hence, a sensible next step is a (conceptual) replication of this effect. Furthermore, it is important to investigate whether the findings hold not only for university students but also for school-age students.

Experiment 2

To address the open question that was mentioned in the preceding discussion, we conducted a second experiment. To replicate the findings of Experiment 1 with respect to prompting, identical conditions (BF plus prompting and BF only) were implemented. We did not include EP-pairs groups because (a) the advantages of fading has been well documented in previous studies, and (b) as shown in Experiment 1, fading and prompting do not interact with each other in terms of learning outcomes.

Besides the conceptual replication of the prompting effect, we tested whether our finding also held for school contexts. Specifically, the participants selected for this experiment were high school students. Against this background, this experiment was designed to address one primary research question: Do self-explanation prompts enhance the learning effect associated with fading?

Method

Participants and design. With parent permission, 40 students (18 males and 22 females) from a southern high school volunteered to participate in this study (mean GPA = 3.41). The participants consisted of 7 sophomores, 22 juniors, and 11 seniors, all of whom were currently enrolled in an advanced algebra course. The participants were randomly assigned in equal proportions (20 per condition) to one of two conditions: BF only or BF plus prompting.

Learning environment. The learning environment used in this experiment was similar to the one used in Experiment 1, with one notable exception: The EP-pairs conditions were no longer available. Instead, the learning environment was reconfigured to run in one of two modes that reflected the two conditions of the present experiment, namely, BF only and BF plus prompting.

Instruments. The instruments used in this experiment were the same as those used in Experiment 1.

Scoring. The scoring of the pretest, anticipative accuracy, near-transfer measure, and far-transfer measure was identical to that of Experiment 1.

Procedure. The procedure of this experiment was similar to that of Experiment 1, with one exception: The present experiment was conducted in a computer classroom equipped with 30 work stations located at the high school from which the students were recruited.

Results

Table 3 presents the means scores and standard deviations for each group on each of the dependent measures. For each dependent measure, an ANCOVA was conducted using the pretest as a covariate ($\alpha = .05$; exception: instructional time). Prior to analy-

Table 3
Study Time and Scores on Each Measure as a Function of Type of Instructional Material (Experiment 2)

	Backward fading					
	No prompting			Prompting		
Measure	*M*	*SD*	Adj. *M*	*M*	*SD*	Adj. *M*
Pretest	4.98	2.22		5.35	1.73	
Accuracy of anticipations	.62	.24	.63	.72	.21	.71
Study time	32.95	9.04		30.85	7.13	
Near transfer	.29	.27	.30[a]	.53	.32	.52[a]
Far transfer	.23	.24	.23[a]	.41	.25	.41[a]

Note. Means in a row sharing superscripts differ statistically. Adj. = adjusted.

sis, each measure was tested for homogeneity of regression, and the results were found to be nonsignificant—all Fs < 2.

Analysis of learning-process measures. There was no significant effect on anticipation, $F(1, 37) = 1.72$, $MSE = 0.4$, $p = .20$. To test for the possibility that the advantage of the prompting group could be attributed to time interacting with the instructional material, we conducted an ANOVA on study time. Although the learners assigned to the no-prompting condition spent slightly more time interacting with the material than their prompting peers, the difference was not statistically significant, $F(1, 38) = 0.56$, $MSE = 67.28$, $p = .46$.

Analysis of learning-outcome measures. ANCOVAs were conducted on near transfer and far transfer. There was a significant effect on near transfer, $F(1, 37) = 6.65$, $MSE = 0.07$, $p < .05$, where the participants who were presented with self-explanation prompts outperformed their peers who did not receive the prompts. Cohen's f statistic for these data yields an effect size estimate of .42 for near transfer, which corresponds to a large effect. The ANCOVA conducted on the measure of far transfer was also significant, $F(1, 37) = 5.14$, $MSE = 0.07$, $p < .05$. The participants who were presented with self-explanation prompts outperformed their peers who did not receive the prompts on far transfer. Cohen's f statistic for these data yields an effect size estimate of .37 for near transfer, which corresponds to a large effect.

Discussion

The results of this experiment clearly indicate that the use of self-explanation prompts in combination with a BF example sequence fosters learning. In particular, this combination appears to not only assist learners in solving problems similar to the ones provided during instruction, but, more important, problems that are structurally different from the instructional material. Moreover, this combination produces a large effect, which indicates that it is also of practical relevance. Finally, as in Experiment 1, the prompting effect had no "time cost"; in other words, it fosters the quality, not the quantity, of example processing.

General Discussion

This research provides additional support for the procedure put forth by Renkl et al. (2002) that entails the use of a fading procedure to structure the transition between studying examples in early stages of cognitive skill acquisition to solving practice problems in later stages. Moreover, this research demonstrates that using a BF procedure fosters the acquisition of rules that can be (more or less) directly applied (i.e., near transfer) as well as those that can be flexibly applied (i.e., far transfer).

The most important message of this article is, however, that a BF procedure can be combined with self-explanation prompting to produce an effect that is both statistically and practically significant. Furthermore, this combined procedure does not increase learning time beyond simply fading alone. Instead, this combination appears to positively influence the quality of example processing without increasing learning time, a learning outcome that we consider to be ideal.

Comparisons With Other Studies

One may also be surprised to learn that our very simple prompting procedure—one that required the learner to only select the underlying principle while not requiring elaborated reflections about the task—produced medium to strong effects on both near and far transfer. In the present study, not only were self-explanations prompted, but feedback about the correctness of the self-explanation was given. Hence, the present effect of our self-explanation procedure is probably due to eliciting self-explanations and to the feedback provided with these explanations. This is not a surprising finding given that the importance of feedback on self-explanations was emphasized recently by Aleven and Koedinger (2002). To understand the exact mechanisms that are impacted by prompting, it would be important to conduct follow-up experiments designed to separate the effects of finding the principle from the effect of providing feedback on the accuracy of principle selection.

Another open question emerges from Conati and VanLehn's (1999, 2000) research that found—in contrast to the present study—very restricted positive effects of a computer-based prompting procedure, one that required the student to select principles or subgoals that corresponded to the actual step. One possible explanation for these conflicting results is that Conati and VanLehn's (1999, 2000) presentation of instructional examples imposed high demands on working memory. Specifically, in their learning environment, the problem formulation and the solution, which each consisted of several boxes, could never be seen at once. To track the learning processes, Conati and VanLehn (1999, 2000) required that the learners move the mouse over one box at a time in order to reveal its contents. Thus, at any given point, only part of the solution was available to the learners. As a result, for the learners to understand the problem in its entirety once they reached the last solution step, they needed to maintain all of the preceding steps in working memory because the steps no longer appeared on the screen. In addition, when the learners wanted to self-explain, they first had to use a series of menus to construct their self-explanation. For example, they first had to decide whether to focus on domain principles or on subgoals before using a browser to search several submenus to complete their explanation. Taken together, the learning environment, including type of self-explanation prompting used by Conati and VanLehn (1999, 2000), may have imposed so much processing demands that many learners may have been cognitively overloaded. The presentation mode and the type of prompting in the present study is a relatively simple one that allows the learners to devote much of their cognitive capacity to gaining understanding. The divergence of the present results from the findings of Hausmann and Chi (2002) can be explained by the fact that they just generally encouraged the students to type comments to themselves. In the present study, in contrast, specific prompts were provided throughout the learning phase.

Theoretical Implications

Our findings on the usefulness of a learning environment that combines fading worked-out steps with self-explanation prompts support the basic tenets of one of the most predominant, contemporary instructional models, namely the cognitive apprenticeship approach (Collins, Brown, & Newman, 1989). This approach suggests that learners should work on problems with close scaffolding provided by a mentor or instructor. This approach is characteristic of Vygotsky's (1978) "zone of proximal development" in which problems or tasks are provided to learners that are slightly more challenging than they can handle on their own. Instead of solving the problems or tasks independently, the learners must rely—at least initially—on the assistance of their more capable peers and/or instructors to succeed. According to this approach, the learners will eventually make a smooth transition from relying on modeling to scaffolded problem solving to independent problem solving. In other words, this model advocates the fading of instructional scaffolding during this transition. Correspondingly, our partially worked-out examples provide a scaffold that permits learners to solve problems they could not successfully solve on their own. The instructional scaffolding—in the shape of worked-out solution steps—is gradually faded in our learning environment.

Reflection is also part of the cognitive apprenticeship process (Collins et al., 1989). That is, learners are encouraged to reflect on their problem-solving process and to try to identify ways of improving it. For instance, they are encouraged to reflect on the problems that they have missed and to try to explain how to generate a correct solution, a process that can increase the likelihood that the correct solution procedure will be internalized by the learner. As the present study suggests, one way of promoting this reflection process is to use prompts that induce self-explanations. In sum, our successful implementation of an arrangement that incorporates Vygotskian-based instructional principles (i.e., scaffolding, reflection) provides additional evidence of its value as basis for modern instructional models.

Practical Implications

One may ask whether it is practical to use the instructional procedures analyzed in this article for teaching skills in well-structured domains. Overall, the use of prompts that encourage the learners to figure out the principle that underlies a certain solution step can be recommended for several reasons, including the following: (a) it produces medium to high effects on transfer performance, (b) these effects are consistent across different age levels (university and high school), (c) it does not interfere with fading, (d) it is very easy to implement (even without the help of computer technology), and (e) it requires no additional instructional time. This prompting procedure is, however, not without its drawbacks. Because this procedure is designed to elicit principle-based explanations, it is ideally suited for well-structured domains such as mathematics and physics that contain clearly identifiable domain principles "under" each solution step—as was the case with our probability examples. As one can imagine, not all domains contain such clearly identifiable principles. Hence, it is worth noting that our prompting procedure can only be applied in an unmodified manner when each solution step can be explained by a principle within the domain. If this is not the case, the prompting procedure could be modified so that the explication of goal–operator combination is the focus, that is, at each worked-out step the learner has to explicate which subgoal is achieved. The research program of Catrambone (1996, 1998) has convincingly shown that elaborating on the goal structure of (well-structured) problems fosters the learner's transfer performance. However, whether this type of prompting in a less structured domain would produce comparable learning effects needs to be tested in future studies.

Open Questions for Further Research

Although the present work resulted in several significant educational insights, it also generated a number of new research questions. Two such questions have already been mentioned in the preceding discussion and refer to the following issues: (a) separation of the effects of finding the domain principles and of feedback on this activity and (b) effects of prompting other types of self-explanation, such as explication of goal–operator combinations.

Another interesting question refers to our decision to prompt only at worked-out steps. As the results of Aleven and Koedinger (2002) suggested, prompting self-explanation during problem solving can also foster learning. Against this background, it might be possible that the prompting effect would even be stronger when the learners are required to name the domain principle at each step, irrespective of whether it is worked out or to be solved. On the other hand, giving principle-based explanation at each step may become a redundant activity that contributes little to learning (cf. Pirolli & Recker, 1994).

Finally, another fruitful goal of future research would be to develop and evaluate versions of our fading and prompting procedures that can be used for studying instructional material containing worked-out examples coupled with practice problems from nonmathematized and less well-structured domains (for first steps in this direction, see Schworm & Renkl, 2002). This would enable us to develop and experimentally test instructional procedures that could be used across a wide range of educational tasks.

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Structuring the Transition From Example Study to Problem Solving in Cognitive Skill Acquisition: A Cognitive Load Perspective

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Cognitive load research has shown that learning from worked-out examples, in comparison to problem solving, is very effective during the initial stages of cognitive skill acquisition. In later stages, however, solving problems is superior. In this contribution, theoretical analyses of different types of cognitive load and their changes over the stages of skill acquisition are presented. Two basic arguments are put forth: (a) Intrinsic cognitive load gradually decreases so that a gradual increase of problem-solving demands is possible without inducing cognitive overload. (b) In contrast to the earlier stages, different learner activities during the later stages constitute either germane or extraneous load, because different instructional goals are to be achieved. Based on these analyses, we propose 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. Empirical evidence supporting this fading procedure is provided, and future research is proposed that focuses on how to ensure that the fading procedure is adaptive to the learners' prior knowledge levels.

In the initial acquisition of cognitive skills in well-structured domains such as mathematics, physics, or programming, learning from worked-out examples is a very advantageous way of learning. It is a learning mode preferred by novices (e.g., LeFevre & Dixon, 1986; Recker & Pirolli, 1995), and it is effective (for an overview, see Atkinson, Derry, Renkl, & Wortham, 2000). While examining techniques to optimize a 3-year mathematics curriculum, Zhu and Simon (1987) found that the entire curriculum could be taught in 2 years—without performance deficits—by employing carefully designed and sequenced worked-out examples. Moreover, studies conducted by Sweller and his colleagues (e.g., Mwangi & Sweller, 1998; Sweller & Cooper, 1985) have shown that example-based learning (with interspersed problems to be solved) is more effective than learning only by problem solving.

However, these findings beg the following question: What precisely does learning from worked-out examples mean? To begin with, worked-out examples usually consist of a problem formulation, solution steps, and the final solution itself. They are typically employed in mathematics textbooks in the following fashion: (a) a principle (or a rule or a theorem) is introduced, (b) a worked-out example is provided, and (c) one or more to-be-solved problems are supplied. Although textbooks tend to use worked examples in this manner, this procedure constituted the control conditions (problem-solving only) rather than the worked example conditions used in studies on the effectiveness of worked examples (e.g., Mwangi & Sweller, 1998; Sweller & Cooper, 1985). In contrast, when we use the notion of "learning from worked-out examples," this procedure indicates that the example phase is lengthened so that a number of examples are presented before learners are expected to engage in problem solving or, alternatively, examples are interspersed with the to-be-solved problems, which is

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an effective format (Mwangi & Sweller, 1998; Sweller & Cooper, 1985). Thus, there is some problem solving involved in example-based learning; however, it is delayed relative to the more traditional problem-solving only procedure.

In later stages of skill acquisition, emphasis is on increasing speed and accuracy of performance, and skills, or at least subcomponents of them, should become automated. During these stages, it is important that the learners actually solve problems as opposed to studying examples. For example, it would be difficult, if not impossible, to become a quick and reliable programmer just by studying worked-out examples containing codes without ever writing a program by oneself.

Although there is little doubt that worked-out examples should be provided initially followed by to-be-solved problems to foster skill acquisition, there remain several open questions. The first question focuses on the issue of how to describe the theoretical status of examples and problems as their respective functions change over the different phases of skill acquisition proposed by cognitive theorists (e.g., VanLehn, 1996). Second, from an instructional point of view, it is unclear how one should structure the transition from example-based learning in the early stages of skill acquisition to problem solving in the later stages.

To address these open questions, we first describe the different phases of skill acquisition proposed by cognitive theorists. Then, we provide a brief description of the various types of cognitive load that are related to skill acquisition followed by a theoretical analysis of how the nature of cognitive load changes from the intermediate to the late stage of skill acquisition. This analysis is followed by the description of a research-supported technique for structuring the transition between these two stages of skill acquisition, a technique that involves the fading of worked-out solution steps. Finally, we conclude with an outlook on future research involving the fading procedure.

COGNITIVE SKILL ACQUISITION

Cognitive skills refer to the learners' capabilities to solve problems from intellectual domains such as mathematics, medical diagnosis, or electronic troubleshooting. Cognitive skill acquisition is, thus, a narrower term as compared to learning. For example, it does not include acquisition of declarative knowledge for its own sake, general thinking or learning skills, general metacognitive knowledge, and so on. In this article, we concentrate on skill acquisition in well-structured domains such as mathematics, physics, and programming. In addition, the cognitive aspects of skill acquisition are focused (for motivational aspects and their interrelation with cognitive issues see, e.g., Alexander, Jetton, & Kulikowich, 1995).

According to a variety of researchers, the process by which cognitive skills are acquired is usually divided into several similar phases, albeit the specifics vary across researchers (e.g., Anderson, 1983; Sweller, van Merriënboer, & Paas, 1998; VanLehn, 1996). From an instructional point of view, VanLehn's (1996) definition of these phases is especially attractive because it dovetails nicely with an example-based process of skill acquisition—a method that is, as already mentioned, very effective.

VanLehn (1996) distinguished among early, intermediate, and late phases of skill acquisition. During the *early phase*, learners attempt to gain a basic understanding of the domain without necessarily striving to apply the acquired knowledge. This phase corresponds to the study of instructional materials (typically texts) that provide knowledge about principles in an example-based skill acquisition process. During the *intermediate phase*, learners turn their attention to learning how to solve problems. Specifically, learning is focused on how abstract principles are used to solve concrete problems. One potential outcome of this phase is that flaws in the knowledge base—such as lack of certain elements and relations as well as misunderstandings—are corrected. In the context of example-based learning, persons first study a sample of examples before turning to problem solving in this phase. Note, however, that the construction of a sound knowledge base is not a quasi-automatic by-product of studying examples or solving problems. In fact, learners have to actively self-explain the solutions, that is, they have to reason about the rationale of the solutions (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Neuman & Schwarz, 1998; Renkl, 1997; VanLehn, 1996). Finally, the learners enter the *late stage* in which speed and accuracy are heightened by practice. During this phase, actual problem solving, as opposed to reflective considerations such as self-explanations, is crucial (Pirolli & Recker, 1994).

Of course, these three stages have no precise boundaries, especially in the case of learners attempting to acquire a complex cognitive skill—one that involves multiple subcomponents. Under these circumstances, learners may be entering the late stage in the acquisition of one of the skill's subcomponents while they are operating in the early or intermediate phase of acquiring the skill's other subcomponents. Thus, learners may be simultaneously in different stages with respect to different parts of a skill.

Returning to the two open questions outlined previously—the changing status of examples–problems over the phases of skill acquisition and structuring the transition from example-based learning in the early stages of skill acquisition to problem solving in the later stages—we now turn our attention to cognitive load theory (CLT) and describe how it provides a useful framework for addressing each question. In the following section, we outline those aspects of CLT that assist us in addressing our open questions.

COGNITIVE LOAD THEORY

Basic Assumptions

CLT focuses on how constraints on our working memory help determine what kinds of instruction are effective.

Working memory is usually characterized as the part of our cognitive architecture in which information that is undergoing active processing is held. This part of our cognitive architecture is considered to have only a very limited capacity. It is usually assumed that only about seven chunks of information can be maintained simultaneously, maybe even less. Moreover, not only is the storage capacity limited in working memory but its ability to process information (e.g., information that has to be compared or organized) is also restricted. Hence, where there are multiple processing demands, working memory capacity may be limited to the simultaneous processing of two or perhaps three chunks.

According to Baddeley (1992), working memory can be differentiated into several interrelated structures. He asserted that there is a central executive structure that controls information processing within working memory. In addition, he proposed that working memory also contains two slave systems: one subsystem for processing visual information (visual–spatial scratch pad) and another subsystem for processing acoustic information (phonological loop). Hence, when there are multiple processing demands, such as the simultaneous presentation of visual and acoustic information, these demands can be distributed by the central executive structure across the respective subsystems thereby helping to maximize working memory's capacity to store and process information.

According to the basic tenets of CLT, one should encourage learning activities that minimize processing and/or storage that is not directly relevant for learning to avoid taxing working memory's limited capacity. To capture this assertion more precisely, three types of cognitive load need to be differentiated (Sweller et al., 1998).

Intrinsic load refers to the complexity of the learning material. More specifically, it refers to the number of elements that the learner must attend to simultaneously to understand the learning material. Element interactivity is high when there are a large number of interacting elements. For example, there is a high-intrinsic load due to high-element interactivity when a novice student studying economics is asked to learn about the mechanisms associated with the vitality of a company's stock because the answer is complicated by the interaction of many factors (e.g., company's profit, expected change in profit, inflation rates, interest rates, etc.). Conversely, in paired-associative learning, intrinsic load is low because a learner in this task can regard each pair independently of the previous pair(s). Of course, the magnitude of intrinsic load is actually dependent on a person's level of prior domain knowledge. High-prior knowledge allows for constructing larger meaningful information chunks so that cognitive load is reduced. Hence, the definition of intrinsic load can be stated more precisely: The complexity of the learning content is relative to a learner's level of prior knowledge.

Germane load refers to demands placed on working memory capacity that are imposed by mental activities that contribute directly to learning. In the case of learning from worked-out examples, self-explanations would be considered as germane load. *Self-explanations* refer to a learner's effort in gaining an understanding of a solution rationale, such as trying to find communalities between two examples. Sweller et al. (1998)—with their focus on schema construction—would have considered this germane load because the act of self-explaining increases cognitive load but directly contributes to schema construction. In a broader sense, however, this type of load can be considered to contribute to whatever is the focus of the learning task (e.g., a relation between concepts and automation of procedures).

Extraneous load is caused by mental activities during learning that do not contribute directly to learning. Again, as in the case of germane load, what constitutes extraneous load depends on the goal of the learning task. For example, when problem-solving schemas should be acquired, extraneous load is imposed if instructional materials contain text and graphics that are difficult to integrate with each other. A learner may use much of his or her cognitive capacity attempting to establish some degree of coherence between the two information sources. Consequently, little or no working memory capacity remains for germane load, particularly if there is also substantial intrinsic load due to the learning material itself. In this situation, learning is likely to be minimal.

Taken together, it is important not to induce high-extraneous load (i.e., load due to activities unrelated to the learning process), especially when it is coupled with high-intrinsic load (due to the characteristics of the material), because the extraneous and intrinsic load may leave only a modicum or no "room" for germane load (i.e., mental activities relevant to learning, such as generating self-explanations). From an instructional perspective, it is especially important to explore ways of specifically fostering germane load (e.g., giving self-explanation prompts).

The Worked-Out Example Effect and its Reversal

These assumptions of CLT are also the basis for explaining the advantage of example-based versus traditional skill acquisition procedures that we described previously. It is assumed that in the beginning of a learning process, the low level of a learner's prior domain knowledge has two consequences: (a) The learner is unable to apply domain- or task-specific solution procedures so, instead, general problem-solving strategies must be employed; and (b) the intrinsic load is high. In this situation, when a learner is confronted with problem-solving demands, he or she usually adopts a means–ends analysis strategy. This strategy demands a substantial portion of working memory capacity because the learner has to maintain the following aspects of the problem in his or her mind: current problem state, goal state, differences between these two states, operators that reduce the differences between the goal state and the present state, and subgoals. Although means–ends analysis can be an effective problem-solving strategy, it unfortunately does not directly foster understanding. Hence, this strategy imposes an extraneous load; as a consequence, there is little or no room left for germane load, such as generating self-explanations that deepen the understanding of the domain. In contrast, when studying worked-out examples, the learner is freed from performance demands, and he or she can concentrate on gaining understanding. In a recent experiment (Renkl, Gruber, Weber, Lerche, & Schweizer, in press), this CLT explanation for the advantage of example-based learning was directly tested by employing a dual-task paradigm. The results of this experiment fully supported CLT.

Although many studies have shown that it is sufficient to reduce extraneous load by employing examples instead of to-be-solved problems to enhance learning (for an overview, see Sweller et al., 1998), it is nevertheless a suboptimal technique when one considers the range of individual differences in example processing. Renkl (1997) showed that most learners do not actively self-explain the solutions of worked-out examples; that is, they do not productively use their free cognitive capacity. Furthermore, Renkl, Stark, Gruber, and Mandl (1998) found that spontaneous self-explanations were not as effective as self-explanations that were enhanced by a short training period provided immediately prior to studying examples. Thus, it is sensible to design instruction that fosters productive self-explanation activity to ensure that the free cognitive capacity that is available in example study is effectively used.

Although examples play an important role in instructional principles derived from CLT, it is also argued that problem solving is superior in later phases of skill acquisition. In a recent study, Kalyuga, Chandler, Tuovinen, and Sweller (2001) analyzed mechanical trade apprentices' learning about relay circuits and their programming in different stages of skill acquisition. Whereas in the initial phase of cognitive skill acquisition, learning from worked-out examples was superior, this advantage faded over time. In fact, the authors found that when learners had ample experience in this domain, learning by solving problems proved to be superior to studying examples. Hence, there was a reversal of the worked-example effect across the phases of skill acquisition (also see Kalyuga, Ayres, Chandler, & Sweller, 2003).

This reversal effect was explained by the so-called *redundancy effect,* one of the primary effects postulated by CLT. Basically, it is argued that worked-out examples contain information that is easily determined by the more experienced learners themselves and, therefore, can be considered redundant. Devoting working memory to redundant information effectively takes away a portion of the learners' limited cognitive capacity that could be devoted to germane load. Moreover, redundant information may even interfere with the schemas constructed by experienced learners.

Our explanation of the worked-out example reversal effect does not contradict the redundancy interpretation. It has, however, a different focus. Whereas the redundancy explanation has its focal point on what is superfluous to the learning task (extraneous load), our account focuses on how the nature of those aspects of the learning activity that constitute germane cognitive load changes across the different phases of skill acquisition.

DIFFERENT TYPES OF COGNITIVE LOAD IN DIFFERENT STAGES OF SKILL ACQUISITION

Whether self-explanations or problem solving impose an extraneous or germane cognitive load varies from the intermediate to the late phase of skill acquisition. In the intermediate phase, the learners are expected to acquire an understanding of the domain and learn how to apply domain knowledge in solving problems. When taking into account the research on how worked examples should be processed, it can be considered crucial that learners actively self-explain the example solutions to themselves (Chi et al., 1989; Renkl, 1997). Active self-explaining is especially important for learners in the beginning of the intermediate phase because they should learn the rationale of how to apply their basic knowledge of the domain that they have gained in the early phase. More specifically, the following self-explanation activities have proven to be crucial:

1. Generation of *principle-based explanations:* A learner assigns meaning to operators by identifying the underlying domain principle, a process that, in turn, fosters a principle-based understanding of an example's solution.
2. *Explication of goal–operator combinations:* A learner assigns meaning to operators by identifying the (sub)goals achieved by these operators, a practice that helps in identifying the goal structure of certain problem types and knowledge of relevant operators.
3. *Noticing coherence:* A learner perceives coherence among examples–problems, an activity that fosters the induction of abstract schemas that enables the learner to solve isomorphic problems even when they contain new surface features.

Hence, in the intermediate phase, germane load corresponds to self-explanations such as principle-based explanations, explication of goal–operator relations, or noticing coherence among different examples in an effort to generalize over surface structures. In the late stage of skill acquisition, the major goal to be achieved is to heighten speed and accuracy. At this juncture, at least subcomponents of the skill should be automated. When automaticity is the goal, self-explanations are not very helpful. Actually solving problems or part of them is the major path by which speed and accuracy can be enhanced.

This claim is backed up by empirical findings. For example, Renkl (1997) found that anticipating solution steps of a worked-out example, which actually is solving part of the problem, is an effective way of learning. However, this appeared to hold true only when the learners had a relatively high level of prior knowledge, that is, when they were further advanced in the course of skill acquisition. Cooper, Tindall-Ford, Chandler, and Sweller (2001) employed an instructional method in example-based learning that induced an activity similar to anticipating. They instructed their learners to imagine a previously learned solution path. Again, as in Renkl's (1997) work, they found that this "mental" problem solving fostered learning only when the learner had a high level of prior knowledge. Finally, Kalyuga et al.'s (2001) already mentioned results—problem solving is superior to example study for advanced learners—are relevant in this context as well.

In summary, when learners proceed in the course of skill acquisition, the introduction of problem-solving elements, such as anticipating and imagining instead of problem solving itself, is productive. When skills should be optimized (in terms of speed and accuracy) and automated, problem solving represents germane load because it directly contributes to these learning goals.

Taken together, it is important to note that what represents cognitive load depends on the specific stage of skill acquisition. More specifically, in the intermediate stage self-explanations constitute an important part of germane load, whereas in the late stage problem solving represents germane load.

STRUCTURING THE TRANSITION FROM THE INTERMEDIATE TO THE LATE STAGE OF SKILL ACQUISITION: FADING WORKED-OUT SOLUTION STEPS

So far, two important propositions can be derived from our CLT assumptions: (a) Intrinsic load gradually decreases over the course of cognitive skill acquisition so that a gradual increase of problem-solving demands is possible without imposing an excessive load. (b) When understanding is acquired, self-explanation activities become extraneous and problem solving is germane, because speed and accuracy should be heightened and automation should be achieved. Hence, problem-solving elements should not be introduced too late because example study and self-explanations are transformed from germane to extraneous load.

Against this background, it is sensible to gradually introduce problem-solving demands after the study of an initial example. This can be accomplished in the following way. First, a complete example is presented (model). Second, an example is given in which one single solution step is omitted (coached problem solving). Then, the number of blanks is increased step by step until just the problem formulation is left, that is, a to-be-solved problem (independent problem solving). In this way, a smooth transition from modeling (complete example) over coached problem solving (incomplete example) to independent problem solving is implemented. This rationale provides one possible answer for structuring the transition from example study to problem solving (for very similar instructional propositions, see van Merriënboer, Kirschner, & Kester, 2003).

An important factor that should contribute to the effectiveness of a smooth transition (fading), as compared to the usual example-based method of using example–problem pairs, is that fading should reduce a heavy cognitive load and, thereby, reduce errors during learning. Under a fading condition, the first problem-solving demand is to generate just a single step, and the demands are only gradually increased. When the goal is to form rules for problem solving, instructional procedures that reduce errors (and immediately correct them if they occur) are most appropriate (e.g., Anderson, Corbett, Koedinger, & Pelletier, 1995). In other words, when the goal is to learn to solve certain types of problems that can be solved by the application of specific to-be-learned rules (near transfer), reducing errors should provide an advantage.

Reducing errors is not, however, necessarily productive when problems should be solved that require the modification of learned solution methods (far transfer). In this case, learned rules cannot be (directly) applied. Far transfer may be fostered by errors that trigger reflections and thereby deepen understanding of the domain (cf. VanLehn, 1996). From this perspective, fading would not foster far transfer performance. However, avoiding the demand to correct errors might reduce the cognitive load that is imposed by problem-solving activities. Cognitive activities that contribute to a deeper understanding of the domain (i.e., self-explanations) might be more likely to occur (Sweller et al., 1998). From this perspective, fading may also foster far transfer performance.

Against this background, we clearly expected that fading worked-out solution steps in contrast to using example–problem pairs fosters performance on near transfer problems (known solution methods). To what extent fading is also favorable for far transfer (new solution methods) was an open question.

As a first step in testing this fading procedure, we conducted a small-scale field study in which we examined whether a fading procedure is more effective than learning by example–problem pairs as they are used in many studies on learning from examples (Renkl, Atkinson, & Maier, 2000; Renkl, Atkinson, Maier, & Staley, 2002; also see Table 1). We compared the learning outcomes of two classrooms (n = 15 and n = 20) from a German Hauptschule (i.e., the lowest track of the German three-track system). In each classroom, a physics lesson (electricity) was conducted in which example–problem pairs or fading examples were employed, respectively. In the fading group, the first task was a completely worked-out example. In the second task, the last solution step was omitted. In the third task, the last two steps were omitted (backward fading of solution steps). Finally, all three steps were left out so that a to-be-solved problem was presented to the learners. In a posttest presented 2 days after the lessons,

TABLE 1
Overview of the Empirical Studies on Fading Worked-Out Solution Steps

Study	*Sample*	*Learning Domain*	*Experimental Comparisons*	*Statistically Significant Fading Effects (Effect Size)*	*Additional Findings*
Quasi-experimental field study on fading	*n* = 35, German low-track students, 9th grade	Physics/electricity	Example–problem pairs versus backward fading	Near transfer: $\eta^2 = .12$	
First lab experiment on fading	*n* = 54, American psychology students	Mathematics/ probability	Example–problem pairs versus forward fading	Near transfer: $\eta^2 = .08$	Near transfer effect: Mediation by reduction of errors during learning
Second lab experiment on fading	*n* = 45, American psychology students	Mathematics/ probability	Example–problem pairs versus backward fading and forward fading	Near transfer: $\eta^2 = .19$; far transfer: $\eta^2 = .12$	Near transfer effect: Mediation by reduction of errors during learning
			Forward fading versus backward fading	Backward fading, less learning time: $\eta^2 = .23$	
Lab experiment on fading + prompting	*n* = 28, American psychology students	Mathematics/ probability	Backward fading without prompting versus backward fading with prompting	Near transfer: $\eta^2 = .18$; far transfer: $\eta^2 = .23$	

the fading group outperformed the example–problem pairs group significantly in near transfer performance but not (significantly) on far transfer (see Table 1). Based on this encouraging result, we conducted two more controlled laboratory experiments to examine the efficacy of a fading procedure relative to learning by example–problem pairs.

In an initial laboratory experiment, 54 American psychology students at a large, southeastern university participated (Renkl et al., 2000; Renkl et al., 2002). They were randomly assigned to the fading or the example–problem condition (*n* = 27 in each group). Two sets of four examples–problems from probability calculation were used, with the examples and problems each consisting of exactly three steps. In this study, we employed a forward-fading procedure (i.e., omitting the first solution step first, then the second, etc.).

We found that the fading procedure clearly fostered near but not far transfer performance. The effect on near transfer was mediated by the lower number of errors committed during the learning phase (see Table 1).

In this laboratory experiment, we conceptually replicated the effectiveness of our fading procedure for near transfer. We obtained this converging result even though this study and our first investigation differed with respect to the type of learners (low-track students vs. university students), the learning domain (physics/electricity vs. mathematics/probability calculation), the learning setting (school lesson vs. computer-based learning in the laboratory), and the kind of fading out worked-out solution steps (backward vs. forward). We interpreted the stability of this finding as an indicator that our fading procedure is reliable and stable despite these very different context conditions.

A caveat remained, however. Because a conceptual replication is not the same as a direct empirical replication, there remained at least some uncertainty whether a direct replication of the findings would also succeed. In addition, an open question arose from the fact that we employed two ways of fading out worked-out solution steps, a backward and forward procedure, across the two experiments. As the context conditions in our two studies varied substantially, we could not compare the relative effectiveness of these two procedures. This comparison was necessary to answer the questions whether the specific type of fading procedure significantly influences learning outcomes or whether it is of minor importance.

To replicate directly the findings of the previous experiment, identical conditions (example–problem pairs and forward fading) were implemented in our second laboratory experiment (see Table 1). In addition, we employed the condition of backward fading in an effort to examine potential differences between the two types of fading. The participants for this study were 45 American students enrolled in several educational psychology courses at a small, northeastern liberal arts college. They were randomly assigned in equal numbers to the forward fading, backward fading, or to the example–problem condition (*n* = 15 in each group).

The positive effect of fading on near transfer was replicated. This effect was again mediated by reduced problem-solving errors during learning. In contrast to our previous studies, we found also a positive effect on far transfer. The statistically significant effect on far transfer was, however, primarily due to the backward-fading condition. Beyond the question of far transfer effects following backward fading, this type of fading procedure was more favorable as compared to forward fading because it was more efficient. The learners in the backward-fading condition spent less time on the examples without disadvantages in transfer performance (see Table 1).

From a cognitive load perspective, the backward-fading condition may be more favorable because the first problem-solving demand is imposed later as compared with forward fading. In the latter condition, the first to-be-determined step might come before the learner has gained an understanding of the step's solution, so that solving the step may impose a heavy cognitive load.

To optimize our fading procedure, in a subsequent laboratory experiment we introduced some self-explanation prompting at the faded steps (Renkl & Atkinson, 2001; also see Table 1). The advantage of worked-out steps is that the learners have enough cognitive capacity left for self-explanation. However, many learners do not effectively use their free capacity; they do not spontaneously provide fruitful self-explanations (Renkl, 1997). The learners' suboptimal self-explanation activities may also be a reason for the somewhat fixed effects of our fading procedure on far transfer in the previous experiments.

We assumed that prompting for self-explanations at the worked-out steps (not at the to-be-determined steps) renders our fading procedure more effective, especially with respect to far transfer. More specifically, we again used probability examples (and problems) and asked the learners to determine at each worked-out step which probability rule was applied. In an experiment, we compared two backward-fading groups with and without self-explanation prompts (n = 14 in each group). We found a strong effect on near transfer and on far transfer in favor of the prompting group (see Table 1). Thus, we showed that employing instructional means to use free cognitive capacity effectively is of major importance.

With respect to research on example-based learning, our four experiments provided the following contributions: (a) A new feature for the design of materials for example-based learning—fading—was introduced that builds a bridge between studying examples in the intermediate phase of cognitive skill acquisition and problem solving in the late stage. (b) In particular, fading as a feature of example-based learning appears to be effective, at least with respect to near transfer. The finding was replicated and shown to be stable across context variables, such as field versus laboratory studies. (c) The number of problem-solving errors plays a role in mediating the effects of fading on near transfer. (d) It is more favorable to fade out worked-out solution steps in a backward manner as compared with a forward manner. (e) Enriching the fading procedure with self-explanation prompting at the worked-out steps fostered not only near transfer but also far transfer.

What do these results tell us about CLT? In our view, there are three main implications: (a) The positive effects of fading on learning outcomes clearly confirm the expertise reversal effect that is postulated in the most recent version of CLT (see Kalyuga et al., 2003). From an instructional point of view, the reversal effect means that after a phase of example study problems to-be-solved should be provided. Our research indicates how to structure the transition between example study and problem solving. (b) Our analysis of which activities induce extraneous or germane load and the corresponding results imply that careful attention has to be devoted to the questions of what the specific learning goal is that is actually pursued (also see Gerjets & Scheiter, 2003). More precisely defined goals than schema construction and schema automation (the learning goals presently emphasized in CLT) are of special importance when instructional procedures should be employed to foster germane load. These procedures can only be tailored appropriately when the learning goal is precisely defined. In our case, research on example-based learning was a supplement to CLT in defining the prompts employed in our prompting experiment. (c) The results of our prompting experiment in particular show that merely reducing extraneous load—which is often the focus of CLT—is suboptimal. More attention should be paid to fostering germane load in future versions of CLT.

FUTURE DIRECTIONS

Although our fading procedure is a sensible method, it can be improved. We argued that, when acquiring a complex skill, a learner may be in the intermediate stage with respect to some subcomponents (i.e., when they still need to be understood), and he or she may be in the late stage with respect to some other subcomponents (i.e., understanding is already reached). From an instructional perspective, it would be optimal to elicit some example study with self-explanations for the former subcomponents and some problem solving for the latter ones. However, the fading procedure used here is not adaptive to an individual learner's level of understanding of different subcomponents. As it is presently structured, the problem-solving demands gradually increase for a prototypical learner. Individual differences in knowledge levels are not considered.

To address this instructional challenge in the future, we intend to examine the effectiveness of two approaches to adapting to a learner's level of prior knowledge: (a) externally determined adaptation, and (b) internally determined adaptation. In the case of *externally determined adaptation*, the learning environment will be designed to diagnose which steps a learner (probably) can or cannot already solve on his or her own. The environment would then provide worked-out solutions for steps that the learner is unable to solve unaided and then fade the steps that the learner is likely to be able to solve on his or her own. In contrast, *internally determined adaptation* will involve training a learner how to engage in productive self-explanation activities. For instance, the learner would be instructed to generate principle-based explanations and engage in the explication of goal–operator combinations while examining the initial example provided in an instructional sequence. With the subsequent examples, the learner would be instructed to first try to anticipate the step and, if this is not possible, to look up the worked-out step and to self-explain by principle-based explanations and explication of goal–operator combinations. Future studies will investigate the feasibility of both forms of adaptation.

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