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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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