Supporting Information Comparisons in Example-Based Hypertext Environments

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Abstract

Global comparisons of learning from hypertext and traditional text have yet failed to show major advantages concerning the effectiveness of hypertext learning. In the current paper it is proposed that an effective hypertext design needs to be based on thorough cognitive task analyses with regard to structures, processes, and resources that are required to benefit from a specific learning approach. This claim is illustrated by two experiments, in which we investigated two methods for supporting effective cognitive processes in example-based hypermedia environments, namely, elaboration prompts and an interactive comparison tool. Both methods improved performance for near-transfer problems. Ways of extending this task-analytical approach to facilitating far transfer are discussed.

Promises and Drawbacks of Hypertext: The Need for Cognitive Task Analyses

Hypertext-based learning environments consist of network-like information structures where fragments of information are stored in nodes that are interconnected by hyperlinks (Conklin, 1987). They are characterized by a high degree of learner control, where users can select information and choose the pacing and sequence of its presentation according to their goals, preferences, and needs.

Several instructional benefits have been postulated for learning from hypertexts from different theoretical perspectives, whereby these perspectives mainly emphasize that hypertext allows for active, constructive, flexible, adaptive, and self-regulated learning. However, they are also characterized by some serious usability problems. Conklin (1987) postulated that *disorientation* (e.g., not knowing how to get to another point in the network) and *cognitive overload* limit the effectiveness of hypertext for learning. The term cognitive overload refers to the assumption that metacognitive or executive skills necessary for hypertext navigation may require cognitive resources that will no longer be available for the pursuit of the currently performed learning task (Niederhauser, Reynolds, Salmen & Skolmoski, 2000). Furthermore, "many learners may not be proficient computer users and must, therefore, use cognitive resources to operate the computer" (Niederhauser et al., 2000, p. 251). According to

the cognitive load theory (Sweller, van Merriënboer & Paas, 1998), these processes may impede learning as they require cognitive resources that may exceed the limits of working-memory capacity. Cognitive load due to the requirements of selecting and integrating information and due to the interaction with the computer (so-called *extraneous cognitive load*) may thus reduce the possible benefits of hypertext-assisted learning (Gerjets, Scheiter, & Tack, 2000). Cognitive resources required by extraneous cognitive load can no longer be devoted to mindful cognitive processes that are associated with a useful type of cognitive load, namely *germane cognitive load*. Rouet and Levonen (1996, p. 20) conclude that "hypertext efficiency involves a trade-off between the power of the linking and the searching tools it provides and the cognitive demands or costs these tools impose on the reader." This may explain why global comparisons of learning from hypertext and traditional text have yet failed to show major advantages concerning the effectiveness of hypertext learning (e.g., Dillon & Gabbard, 1998). From a cognitive load perspective, an important objective of instructional design with regard to hypertext-assisted learning is thus to minimize extraneous cognitive load and to stimulate learners to invest cognitive resources in activities that result in germane cognitive load.

To achieve this objective, much more detailed analyses of the relevant cognitive processes and resources involved in a specific learning situation are needed in order to predict under which conditions hypertext environments will be beneficial or harmful for learning (cf. Gerjets & Hesse, 2004). Much of the early research on hypertext learning can thus be criticized for comparing learning from text and hypertext in a very general way, without specifying the learning approach chosen and the cognitive structures, processes, and resources necessary to benefit from this learning approach. Without these specifications, findings with regard to the relative superiority of hypertext or text are of rather limited value as it is not clear whether these findings might generalize over different learning approaches. In our own research we thus try to combine hypertext experiments with cognitive task analyses in order to compare instructional conditions that differ in the cognitive processes that they support or require and in the cognitive resources needed.

The learning approach in the presented studies focuses on the acquisition of problem schemas from worked-out examples. For this learning approach, research literature is available that addresses the cognitive processes involved as well as the cognitive resources needed for successful learning. Furthermore, pivotal cognitive processes in schema acquisition from worked-out examples are comparison processes and elaboration processes. As will be outlined in the following, these processes seem to be particularly apt for hypertext-assisted learning.

Example-Based Hypertexts and Schema Acquisition: A Task-Analytic Approach

It has often been argued that probably the most important prerequisite for successful problem solving consists in the availability of abstract *problem schemas*, that is, representations of *problem categories* together with category-specific *solution procedures*. Schemas highlight *structural problem features* that determine a problem's category membership and detach these structural features from merely incidental and irrelevant *surface features* of the domain context or cover story. Because of their abstract nature, schemas allow to efficiently solve problems that belong to one of the represented problem categories. Once a problem has been identified as belonging to a known problem category, the relevant schema is retrieved from memory and information that is specific to the problem is filled into the slots of the schema. Finally the category-specific solution procedure attached to the schema is executed in order to solve the problem.

With regard to the acquisition of problem schemas, studying worked-out examples (i.e., example problems together with a step-by-step solution) seems to be superior to actively solving training problems – at least in initial skill acquisition (cf. Atkinson, Derry, Renkl & Wortham, 2000). It has, however, also been shown that the mere availability of examples is not sufficient to guarantee the acquisition of appropriate schemas. Rather, students have to deploy profitable strategies of processing worked-out examples, that is, elaborations and comparisons of examples.

A commonly found problem in skill acquisition from worked-out examples is that learners "tend to form solution procedures that consist of a long series of steps – which are frequently tied to incidental features of the problems" (Catrambone, 1998, p. 355). To overcome these shallow representations of solution procedures, learners have to *elaborate examples* by drawing inferences concerning the structure of example solutions, the rationale behind solution procedures, and the goals that are accomplished by individual solution steps (e.g., by relating example-specific information to more abstract information; e.g., Renkl, 1997). Without example elaborations, transfer difficulties might result when learners attempt to solve novel problems that do not fall into known problem categories and that require an adaptation of procedures illustrated by examples.

Moreover, learners need to *compare different examples* in order to notice structural features that differ among problem categories and that are shared by all problems within a category. Comparing examples within and among categories with regard to their differences and similarities might allow learners to identify the relevant features of worked-out examples and to avoid confusion due to examples' surface features (Quilici & Mayer, 1996). Without these comparison processes learners might tend to categorize test problems according to their surface features and in turn tend to apply inappropriate solution procedures to them. Two different types of example comparisons can be distinguished, namely, within- and across-category comparisons, which will be described in the following section.

Bernardo (1994, p. 379) proposes "that problem-type schemata are acquired through some inductive or generalization process involving comparisons among similar or analogous problems of one type." Therefore, it has often been advocated to provide learners with *multiple examples for each problem category* (e.g., Quilici & Mayer, 1996) so that they can *compare examples within problem categories* with regard to their differences and similarities. From these comparisons, learners can infer that shared properties of examples from the same category may potentially be the structural features that determine a problem's category membership. Additionally, comparisons within a problem category may enable learners to identify surface features that vary between the category's examples and that are therefore obviously irrelevant with regard to the applicability of the solution principle attached to this problem category. Thus, by comparing multiple instances within a category with regard to their commonalities and differences, all example features can be hypothetically classified as either being structural or surface features. Despite the fact that many researchers advocate the provision of multiple examples, there is not much empirical evidence to support this claim. In particular, there is a lack in studies that directly compare single- and multiple-example conditions. An exception to that is a study conducted by Quilici and Mayer (1996). However, contrary to their initial expectations they found no performance differences between single-example and multiple-example conditions. In line with these findings, we could demonstrate in our own studies that there are promising example-processing strategies that rely on *single examples per problem category* and that are as effective for schema acquisition as comparing multiple examples within categories, namely *comparing examples across problem categories* (Scheiter & Gerjets, 2005). However, in order to have learners profit substantially from across-category comparisons, the surface features of examples have to be kept constant across categories in order to allow learners to recognize that these surface features are not suitable to determine a problem's membership to a specific category. From these across-category comparisons, learners can infer that only *properties that differ between the examples* may potentially be the *structural features* that determine a problem's membership to a specific category.

We hypothesize that the linking capabilities of hypertext environments and the resulting distributed information representation may support *example comparisons and example*

elaborations by providing *navigational affordances* for them (thereby increasing germane cognitive load). In contrast to linear structures, each information unit can be explicitly related to a large number of other units by means of hyperlinks, which should encourage example comparisons as well as elaborations and thus aid schema construction. However, the same hypertext features might also impose extraneous cognitive load on the learner. For instance, a distributed information representation might cause split-attention effects where learners must integrate different sources of information simultaneously (Sweller et al., 1998). This has to be taken into account when designing example-based hypertext environments.

Results of Previous Experiments with Example-Based Hypertext Environments

To test the instructional potential of example-based hypertext environments for supporting schema acquisition, Gerjets et al. (2000) studied whether learners were able to use the linking capabilities to engage in example comparisons and elaborations. The hypertext used taught learners how to solve probability problems. All learners could retrieve abstract explanations on six problem categories. As a first independent variable the availability of worked-out examples that illustrated the abstract information was manipulated. Learners had the opportunity to either study no, one or three worked-out example(s) with different surface features for each problem category. All examples in the one-example condition were couched in the same cover story. As a second independent variable learners with low and high domain-specific prior knowledge were distinguished.

The results showed that whereas prior knowledge had a significant impact on later problem-solving performance, participants did not differ in performance as a function of whether they could retrieve zero, one, or three examples. However, more detailed analyses of example-processing strategies revealed that mindfully processing these examples was strongly predictive for performance. In particular, learners who processed the examples carefully in the one-example condition and learners who retrieved more than one example per category in the three-examples condition showed better performance than participants who displayed a less intensive example-processing behavior. Moreover, the profitability of different example-processing strategies was moderated by prior knowledge. Low prior knowledge learners benefited only from carefully studying single examples per category, whereas for high prior knowledge learners comparing multiple examples for each problem category was also effective. Moreover, other prior studies (Scheiter & Gerjets, 2005) showed that learning from multiple examples may even be harmful if learners do not process these examples appropriately. Single examples are probably less vulnerable to effects of inappropriate, that is, not sufficiently intense processing of examples, because there is less information to process from the very beginning.

Based on these experimental findings and on the task-analytic considerations elaborated in the previous section we developed and evaluated two instructional devices that were intended to stimulate learners' processing of single examples per problem category. Experiment 1 investigates the effects of processing prompts that provided learners with instructional guidance on how they should relate example-specific information to the more abstract information (i.e., example elaborations). Experiment 2 investigates the effects of an interactive comparison tool that was designed to stimulate learners to engage in across-category comparisons.

Experiment 1: Processing Prompts

In order to stimulate learners' processing of single examples per problem category we combined the hyperlinks for retrieving worked-out examples with processing prompts that were intended to scaffold learners' interaction with the examples. Processing prompts have been used successfully in other studies to elicit specific self-explanation activities in learners (cf. Conati & VanLehn, 2000). We assumed that these prompts would be particularly helpful for learners with a low level of prior knowledge, who benefited most from single examples in the study by Gerjets et al. (2000).

Method

Participants Eighty university students participated in this study (average age 24.3 years, 48 female, 32 male).

Materials and Procedure For experimentation the hypertext-based learning and problem-solving environment HYPERCOMB on combinatorics was used (for details cf. Gerjets, Scheiter, & Schuh, 2006). Subsequent to a short introduction to the domain of combinatorics, participants could use an example-based learning environment that allowed learners to select and sequence instructional materials by means of a navigation bar that was permanently visible. This navigation bar contained links to each of six problem categories. Whenever a participant clicked a hyperlink, first the abstract information was displayed. The abstract information page additionally contained one hyperlink that enabled the retrieval of an urn example for the illustration of the problem category in question. Whenever a participant had clicked on an example-hyperlink, the example together with a step-by-step solution was displayed on a single page. After having processed this example, participants could either go back to the abstract information page or they could switch to another problem category by clicking one of the six hyperlinks in the navigation bar. Thus, the linking structure used in HYPERCOMB provided affordances to compare examples across categories as well as to compare examples with abstract information. In order to allow learners to draw substantial inferences with regard to structural problem features from these comparisons, we used the same cover story across problem categories (i.e., selecting marbles from an urn). Participants could decide by themselves when to quit the learning phase and when to start working on the test problems.

Design and Dependent Variables As a first independent variable the availability of processing prompts as a between-

subject factor was varied. Learners with processing prompts received the following annotation of the hyperlink on the abstract information page: "You can access a simple urn example in order to better understand this solution procedure. This example is very helpful in clarifying the principle of <NAME OF PROBLEM CATEGORY>. The example can help you to understand how to apply the formula. Read the example thoroughly and especially pay attention on how to determine the value of the variables *n* and *k*". Moreover, an example page could only be left after learners had confirmed that they had understood the information by clicking a respective link. Domain specific prior knowledge (low vs. high) according to a median split within the two prompting conditions served as the second independent variable (multiple-choice pretest at the beginning of the experiment).

As dependent variables, the problem-solving performance for three isomorphic test problems (in percentage correct) as well as the mean time spent per example retrieved were obtained. The mean time spent per example retrieved was registered in order to investigate whether the prompts prolonged the processing of individual worked-out examples.

Results

The data (Table 1) were analyzed by a 2-factorial analysis of variance (prior knowledge x processing prompts). Moreover, as the learners' gender had turned out to be significantly correlated with problem-solving performance in prior experiments, we used this variable as a covariate. The analysis of problem-solving performance revealed better learning outcomes for learners with high prior knowledge ($F(1,75) = 8.09$; $MSE = 304.61$; $p < .01$; $\eta^2 = .09$). Additionally, the provision of processing prompts led to a marginally significant improvement in problem-solving performance ($F(1,75) = 3.62$; $MSE = 304.61$; $p = .06$; $\eta^2 = .04$). There was no interaction ($F(1,75) = 2.07$; $MSE = 304.61$; $p > .10$; $\eta^2 = .02$). Subsequent specific contrasts revealed that processing prompts were especially beneficial for learners with low prior knowledge ($t(38) = 2.13$; $p < .05$, one-tailed), while they had no reliable impact on the problem-solving performance of learners with high prior knowledge ($t(38) = 0.22$; $p > .40$, one-tailed). To test whether the impact of processing prompts on problem-solving performance was moderated by a more intensive example processing, we analyzed the time spent per example retrieved. Processing prompts resulted in the expected increase in study time ($F(1,75) = 6.20$; $MSE = 400.99$; $p < .05$; $\eta^2 = .06$); there was

neither a main effect of prior knowledge, nor an interaction (both $Fs < 1$).

To conclude, annotating hyperlinks with specific processing prompts is a suitable instructional device to intensify the elaboration of worked-out examples and to stimulate learners to relate example-specific information to more abstract information on different problem categories. This improved problem-solving performance particularly for low prior knowledge learners.

Experiment 2: Interactive Comparison Tool

Experiment 2 was designed to test the effectiveness of a hypertext-based comparison tool for engaging learners in comparing worked-out examples across problem categories.

Method

Participants Thirty one high-school pupils participated in this study (average age 14.0 years, 14 female, 17 male).

Materials and Procedure Prerequisite knowledge was measured by a pretest on important concepts necessary to solve algebra word problems (e.g., rules for operating with fractions). Subsequently, the pupils used a hypertext environment, which conveyed knowledge on how to solve algebra word problems. They were asked to study three computer-based textbook chapters on biology, chemistry, and politics. Embedded in each of the three chapters were three algebraic worked-out examples that illustrated how to solve specific problems in these domains (e.g., damage rates of different types of trees, mixing liquids, rules about the election process of the German parliament). Depending on the experimental condition either only the examples were presented or they were followed by an interactive comparison tool for across-category comparisons. Within each chapter, the three examples differed with regard to the problem category they belonged to and thus required a different algebraic solution formula. The three formulas were identical across the three school subjects. In the subsequent test phase pupils had to solve algebraic word problems on paper. The overall time for learning and problem solving was restricted to 120 minutes.

Design and Dependent Measures A 2x4-factorial design was used with the between-subject factor "comparison tool" and the within-subject factor "transfer distance". Learners

Table 1: Results as a function of the provision of processing prompts and the level of prior knowledge (Exp. 1).

	Without processing prompts		With processing prompts	
	Low PK (n = 20)	High PK (n = 20)	Low PK (n = 20)	High PK (n = 20)
Prior knowledge (% correct)	35.75	70.30	36.35	68.10
Problem-solving performance (% correct)	50.83	67.22	63.89	68.33
Time spent per example retrieved (in sec)	39.00	42.44	50.60	53.34

without comparison tool were presented only with the text-based worked-out examples. Learners with comparison tool additionally had available an interactive comparison tool after they had studied the nine worked-out examples. This comparison tool was based on hyperlinks and pop-up windows that allowed learners to quickly compare the three structural different worked-out examples from the biology domain with regard to their similarities and differences. Whenever learners clicked on one of the three comparison links, two pop-up windows displayed the examples to be compared directly aligned to each other. We used multiple pop-up windows to create an integrated presentation thereby avoiding split attention.

As a second independent variable four levels of transfer distance were constructed for the 21 test problems that learners had to solve subsequent to the learning phase, to assess the differential effectiveness of the comparison tool. Equivalent problems shared surface as well as structural features with the worked-out examples. Isomorphic problems shared only structural features with the worked-out examples, but were embedded in different cover stories. Equivalent and isomorphic problems both required near transfer only, because the solution formula presented during learning could be used without modification to solve these problems. Similar problems shared only surface features with the worked-out examples but differed with regard to their structural features. Thus, similar test problems can be described as novel problems that require far transfer in that known algebraic solution formulas have to be modified to be applicable to these problems. Unrelated problems neither shared surface nor structural features with the examples and were thus novel problems, too. Learners' performance for solving the 21 problems (in % correct) was registered as a dependent measure. We analyzed the percentage of equivalent, isomorphic, similar, and unrelated test problems solved.

Results

Analyzing learners' problem-solving performance (Table 2) by an ANOVA (comparison tool x transfer distance) yielded a main effect in favor of the comparison tool ($F(1,29) = 467.87$; $MSE = 1010.38$; $p = .05$; $\eta^2 = .13$).

Table 2:Performance (% correct) as a function of the comparison tool and transfer distance (Exp. 2).

	Comparison tool	
	No (n = 16)	Yes (n = 15)
Prerequisite knowledge	89.06	87.78
Equivalent problems	75.78	93.17
Isomorphic problems	64.06	79.33
Similar problems	46.50	55.20
Unrelated problems	37.50	42.67

Additionally, performance depended on transfer distance ($F(3,87) = 59.46$; $MSE = 208.96$; $p < .001$; $\eta^2 = .64$). There was no interaction ($F(3,87) = 1.20$; $MSE = 208.94$; $p > .30$; $\eta^2 = .11$). Specific contrasts for the four levels of transfer distance revealed that the comparison tool improved performance for equivalent problems ($t(29) =$

2.68; $p < .01$, one-tailed) and isomorphic problems ($t(29) = 1.81$; $p < .05$, one-tailed), but did not affect solving similar problems ($t(29) = 1.27$; $p > .10$, one-tailed) or unrelated problems ($t(29) = 0.72$; $p > .20$, one-tailed). Thus, the experiment demonstrates that an interactive comparison tool helps learners to abstract from irrelevant surface features by having them compare examples that share the same cover stories across problem categories. This facilitates later problem-solving performance particularly for solving near transfer problems.

Summary and Discussion

In this paper we have argued that the development of powerful and effective hypertext environments for learning should be based on a strong theoretical foundation in detailed cognitive task analyses with regard to the structures, processes, and resources involved in specific learning approaches that are to be supported by hypertext technology. Only then "hypertext can enhance learning. It does so by presenting environments that offer greater opportunities for students to engage in the type of cognitive activities recognized by theorists as encouraging learning" (Shapiro & Niederhauser, 2004, p. 618).

In the experiments reported in this paper we focused on the learning approach of using worked-out examples for the acquisition of problem schemas. For this learning approach, there are a couple of research findings that address the cognitive processes involved as well as the cognitive resources needed for successful learning. Based on these findings, pivotal cognitive processes in schema acquisition from worked-out examples are elaboration processes and comparison processes that seem to be particularly apt for hypertext-assisted learning. In Experiment 1 we demonstrated that annotating hyperlinks for retrieving worked-out examples with processing prompts intensified the elaboration of worked-out examples by stimulating learners to relate example-specific information to more abstract information on different problem categories. This stimulation of cognitive processing improved problem-solving performance particularly for learners with low prior knowledge. In Experiment 2 we provided evidence for the effectiveness of an interactive comparison tool that encouraged learners to compare worked-out examples with common surface features across problem categories. The comparison tool facilitated later problem-solving performance particularly on near transfer problems.

From a theoretical perspective, both instructional devices implemented in Experiment 1 and 2 mainly aimed at helping learners to abstract from irrelevant surface features of examples and to construct appropriate problem schemas. This schematic knowledge is, however, tied to the boundaries of problem categories. Accordingly, both instructional devices mainly improved performance for near-transfer problems, which originate from the same categories as the examples previously studied.

Improving far-transfer performance would require additional instructional support that allows learners to go below the schema level and to understand the rationale of individual solution steps. One promising avenue to support learners in this type of reasoning is to embed dy-

namic visualizations within an example-based hypermedia environment. For instance, we used task-analytic methods to design dynamic visualizations that depict the initial problem state as well as changes to this problem state resulting from applying a solution step. We studied these visualizations in the domain of combinatorics (Scheiter, Gerjets & Catrambone, 2006) as well as in the domain of algebra (Schuh, Gerjets & Scheiter, 2005) and could demonstrate that they have the potential to particularly foster learners' far-transfer performance. However, there is evidence that not every visualization is similar effective. The best learning outcomes with regard to far-transfer performance resulted from dynamic visualizations that initially depicted the examples' concrete objects and than visually showed the transition from a concrete problem statement to an abstract mathematical representation of the problem and its solution. Thus, the effectiveness of the visualizations seems to reside in the fact that they help learners to translate a concrete example into an abstracted representation, based on which mathematical operations can be carried out more easily. Accordingly, the main methodological claim on designing hypertext structure advocated in this paper apparently also applies to the issue of augmenting hypermedia environments with dynamic visualizations. Namely, it is not enough to merely postulate some general advantages of some particular instances of educational technology in quite broad terms. Instead, detailed cognitive task analyses with regard to structures, processes, and resources are required to guide the development of powerful and effective learning environments (cf. Gerjets & Hesse, 2004).

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