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Authors
Gerjets, Peter
Scheiter, Katharina
Catrambone, Richard

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Peter Gerjets (p.gerjets@iwm-kmrc.de)
Multimedia and Hypermedia Research Unit, Knowledge Media Research Center
Konrad-Adenauer-Strasse 40, 72072 Tuebingen, Germany

Katharina Scheiter (k.scheiter@iwm-kmrc.de)
Department of Applied Cognitive Psychology and Media Psychology, University of Tuebingen
Konrad-Adenauer-Strasse 40, 72072 Tuebingen, Germany

Richard Catrambone (rc7@prism.gatech.edu)
School of Psychology, Georgia Institute of Technology
Atlanta, Georgia 30332-0170, USA

Abstract

In this paper, we provide evidence against the common idea that worked examples should be designed to convey problem categories and category-specific solution procedures. Instead we propose that instructional examples should be designed in a way that supports the understanding of relations between structural problem features and individual solution steps, i.e. relations that hold below the category level. We illustrate in the domain of probability word problems how category-avoiding instructional examples can be constructed. In two experiments we provide evidence that category-avoiding examples reduce cognitive load during learning and that they foster subsequent problem-solving performance.

Problem-Type Schemata and Skill Acquisition

It has often been argued that one important prerequisite for skilled problem solving in well-structured and knowledge-rich domains (e.g., physics, mathematics or programming) is the availability of *problem-type schemata* (Gick & Holyoak, 1983; Reed, 1993), i.e., representations of problem categories together with category-specific solution procedures. Once a problem has been identified as belonging to a known *problem category* the relevant schema is retrieved from memory, is instantiated with the information that is specific to the to-be-solved problem, and finally the *category-specific solution procedure* attached to the schema is executed in order to produce a solution to the problem (cf. Derry, 1989).

Schema-based problem solving is considered to be very efficient and therefore often seen as a marking feature of experts' problem solving (VanLehn, 1996). Accordingly, a substantial amount of research has focused on the question of how such schemata can be acquired. A ubiquitous answer to this question is that *studying concrete instances* of problem categories (i.e., examples) is necessary for schema acquisition (Atkinson, Derry, Renkl, & Wortham, 2000; Sweller, van Merriënboer, & Paas, 1998).

Schema Acquisition from Worked Examples

In particular worked examples (i.e., example problems together with a step-by-step solution) play an important role in schema acquisition (cf. Atkinson et al., 2000). However, the mere availability of instructional examples seems not to be sufficient to guarantee an adequate representation of problem categories and an understanding of category-specific solution procedures. Rather, a profitable processing of worked examples has to be ensured. Such processing is likely to include example comparisons and example elaborations as the most important activities. Many approaches to improve the instructional design of worked examples subscribe to the general doctrine of using worked examples as a means of conveying problem categories and their associated solution procedures by fostering these activities.

Example comparisons: Providing multiple examples allows a learner to compare examples within and among problem categories with regard to their differences and similarities. These comparisons might enable learners to identify the defining features of problem categories and to avoid confusions by examples' surface features (Cummins, 1992; Quilici & Mayer, 1996). According to Bernardo (1994, p. 379) there is "a consensus that problem-type schemata are acquired through some inductive or generalization process involving comparisons among similar or analogous problems of one type." Without these comparison processes learners might tend to categorize test problems according to their surface features and in turn to apply inappropriate solution procedures to them.

Example elaborations: A commonly found problem 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 – rather than more meaningful representations that would enable them to successfully tackle new problems" (Catrambone, 1998, p. 355). To overcome these shallow representations of solutions, learners have to draw inferences concerning the structure of example solutions, the rationale behind solution procedures, and the goals that are accomplished by individual solution steps. In order to foster an understanding of category-specific solution procedures several methods have been suggested. One is that solution steps can be *grouped according to their subgoals* (Catrambone, 1998), which is thought to provide affordances for learners to self-explain the meaning of individual solution steps (Chi, Bassok, Lewis, Reimann, & Glaser, 1989). A second is that *instructional explanations* can be introduced to supplement self-explanations generated by the learner (Renkl, 2002). Both methods aim at overcoming the *transfer problem* that frequently occurs when learners attempt to solve novel problems that do not fall into known problem categories and that require an adaptation of the procedure illustrated by worked examples.

However, even when using the abovementioned instructional devices, it remains difficult for learners to recognize problem categories and to understand their associated solution procedures. Therefore, we have begun exploring a more radical approach to the design of useful instructional examples in this paper by abandoning the general idea that worked examples should aim at conveying problem categories and category-specific solution procedures. We are experimentally comparing traditional *category-focusing examples* with *category-avoiding examples.* Our results shed some general doubts on the instructional approach of using the concept of problem-type schemata as a basis for tailoring example-based instruction.

What we mean by category-avoiding examples in contrast to category-focusing examples will be illustrated in the next two sections in the domain of probability word problems Probability word problems deal with calculating the probability of individual and complex events. The probability of some individual event in a random experiment can be calculated by dividing the number of acceptable outcomes by the number of possible outcomes. A series of random experiments - where each random experiment consists of a selection process that yields one individual event – results in a complex event. How the probability of complex events is calculated can be explained by either using a category-focusing example format or a category-avoiding example format (for an illustration see Table 1).

Table 1: Category-focusing and category-avoiding instructional examples used for experimentation

100M-SPRINT EXAMPLE At the Olympics 7 sprinters participate in the 100m-sprint. What is the probability of correctly guessing the winner of the gold, the silver, and the bronze medals?	
CATEGORY-FOCUSING EXAMPLE	*CATEGORY-AVOIDING EXAMPLE*
IDENTIFY TASK FEATURES This problem is a **permutation-without-replacement** problem. Problems of this type have two important features: First, the **order of selection is important**, and second, there is **no replacement of selected elements**. We are not interested only in finding out just which 3 of the 7 sprinters win medals, rather we want to know specifically which sprinter wins which medal. Therefore, the order of selection matters. A sprinter can win at most only one medal. Thus, this problem is a problem without replacement. That is, after a sprinter wins a medal he is not eligible for being selected again. **APPLY FORMULA** For this type of problem the following formula should be applied: **A = n!/(n-k)!** with *n* being the number of all sprinters and *k* being the number of sprinters that have to be correctly guessed. **INSERT VALUES** In the given example there are 7 sprinters to choose from. This is the set of elements for selection (n = 7). As we want to find out the probability of correctly guessing the winner of the gold, the silver, and the bronze medals, 3 sprinters out of these 7 sprinters have to be selected. Therefore, the number of selected sprinters equals k = 3. Inserting these values into the formula for permutation without replacement yields **7! / (7- 3)! = 210 possible permutations**. **CALCULATE PROBABILITY** In order to calculate the probability of correctly guessing the winner of each of the three medals, divide 1 (the particular permutation we are interested in) by the number of possible permutations. Thus, the probability of getting this permutation (the winner of each of the three medals) equals **1/210**.	**FIND 1ST EVENT PROBABILITY** In order to find the first event probability you have to consider the number of acceptable choices and the pool of possible choices. The number of acceptable choices is 1 because only 1 sprinter can win the gold medal. The pool of possible choices is 7 because 7 sprinters participate in the 100m-sprint. Thus, the probability of correctly guessing the winner of the gold medal is **1/7**. **FIND 2ND EVENT PROBABILITY** In order to find the second event probability you again have to consider the number of acceptable choices. The number of acceptable choices is still 1 because only 1 sprinter can win the silver medal. The pool of possible choices is reduced to 6 because only the remaining 6 sprinters participating in the 100m-sprint are eligible to receive the silver medal. Thus, the probability of correctly guessing the winner of the silver medal is **1/6**. **FIND 3RD EVENT PROBABILITY** In order to find the third event probability you again have to consider the number of acceptable choices. The number of acceptable choices is still 1 because only 1 sprinter can win the bronze medal. The pool of possible choices is reduced to 5 because only the remaining 5 sprinters participating in the 100m-sprint are eligible to receive the bronze medal. Thus, the probability of correctly guessing the winner of the bronze medal is **1/5**. **CALCULATE THE OVERALL PROBABILITY** The overall probability is calculated by multiplying all individual event probabilities. Thus, the overall probability of correctly guessing the winner of each of the three medals is **1/7 * 1/6 * 1/5 = 1/210**.

Note: In experimental conditions with instructional explanations the example solutions contained all information stated in the respective table column. Conditions without instructional explanations contained only the information printed in bold.

Category-Focusing Examples

As has been already noted by Atkinson and Catrambone (2000), mathematical problem solving is often characterized by "computationally-friendly" solution approaches in which multiple solution steps are collapsed into a single formula. Although these formulas might allow one to easily calculate solutions by simply inserting the correct variable values there are also serious drawbacks to this approach. Most importantly, formulas are usually restricted to solving a narrow range of problems that fall into predefined problem categories corresponding to the solution formula.

Like many topics, the calculation of complex-event probabilities is usually taught by means of this type of category-specific solution formulas. The approach is to calculate the probability of complex events by dividing the number of acceptable complex events by the number of possible complex events. Category-specific solution formulas are needed for calculating the number of possible complex events. In the materials used for experimentation we distinguish between four different problem categories (permutations and combinations, each with and without replacement) that differ with regard to two structural features: The first is, whether the *order in which elements are selected* is important, the second is, *whether selected elements are replaced* after selection. The solution procedure based on these categories comprises four steps that are illustrated in the category-focusing example in the left column of Table 1, namely (1) identify task features, (2) apply formula, (3) insert values, and (4) calculate probability.

This solution approach is a convenient and fast way of calculating complex-event probabilities. Category-focusing examples are well suited to explain how to categorize problems and apply category-specific solution formulas. However, there are at least two difficulties in learning with these category-focusing examples: cognitive load and molar representations of solution procedures.

Studying category-focusing examples usually requires learners to consider multiple structural problem features at the same time in order to understand the problem's category membership. During schema acquisition all information units that are to be integrated into that schema have to be simultaneously activated in working memory (Sweller et al., 1998). Therefore, category-focusing examples may result in substantial *cognitive load* depending on the number of structural problem features that have to be kept in mind concurrently. Unfortunately, cognitive load prevents learners from engaging in profitable processes of comparing and elaborating examples that might be necessary for understanding problem categories and solution procedures.

Category-focusing examples typically result in a *molar representation of solution procedures*. For instance, one has to have knowledge on all defining structural features of a problem before being able to decide on a formula needed for its solution. Therefore, relations below the category level might be poorly understood, i.e., relations holding irrespective of category membership such as relations between structural problem features and individual solution steps. As a result, learners may not acquire the knowledge necessary to directly translate individual structural problem features into characteristics of the problem solution in a modular way. Consequently, they might fail to adapt solution procedures to novel problems beyond the known problem categories. Based on these concerns we developed a category-avoiding example format that does not require learners to consider multiple structural problem features simultaneously and that focuses on individual solution steps and their relation to individual structural problem features across the boundaries of problem categories.

Category-Avoiding Examples

Compared to traditional "molar" examples the category-avoiding examples we constructed are "modular" because solution procedures are broken down into smaller meaningful groups of solution steps that can be understood in isolation and that can be separately transferred when solving novel problems. This format should help learners to organize their problem-solving knowledge in a way that is independent of problem categories and generalizes across problems in a domain. In this respect, category-avoiding examples conform to the subgoal learning model that proposes to group sets of solutions steps according to the subgoals they aim to achieve in the solution procedure (Catrambone, 1998). This approach aims at conveying general problem-solving strategies that apply at the level of individual solution steps and that might allow learners to derive solutions for different types of problems on their own.

In order to explain the calculation of complex-event probabilities without referring to problem categories we relied on the fact that problems in probability theory can be solved by breaking down complex events into sets of individual events. The solution procedure based on this category-avoiding approach comprises four steps that are illustrated in the category-avoiding example in the right column of Table 1. In this example the probability of a complex event is calculated by determining the probabilities of all individual events that make up the complex event (step 1 to 3) and then multiplying these individual-event probabilities to calculate the overall probability (step 4).

When calculating a particular individual-event probability one has to take into account how the number of possible and acceptable choices change from the preceding to the current trial. These changes depend on whether previously selected objects are *replaced or not* after having been selected and on *whether there is more than one acceptable choice* in a given trial. The fact that these two questions correspond to the structural features of the probability problems makes it easier to adapt this approach to novel problems. The solution procedure illustrated by category-avoiding examples does not require one to categorize problems before solving them. Rather, decisions with regard to individual structural problem features can be directly translated into modifications of individual solution steps (i.e., changes of possible and acceptable choices from trial to trial). The reasoning exemplified in the category-avoiding examples thus should help learners to understand relations below the category level that hold irrespectively of category membership.

Assumptions with regard to the relative effectiveness of the two example formats were tested in two experiments that will be described in the remainder of the paper.

Overview of Experiments

Experiment 1 was a preliminary study to test whether category-avoiding examples lead to better problem-solving performance for isomorphic as well as for novel problems. This was expected because category-avoiding examples (1) should reduce cognitive load during learning thereby allowing cognitive resources to be devoted to profitable example processing and, (2) should foster an understanding of how structural problem features translate into individual solution steps. Experiment 1 is only roughly sketched as the focus of the paper is on Experiment 2. In Experiment 2 we tried to directly test whether category-focusing examples are associated with a higher level of cognitive load. Additionally, we explored the role of instructional explanations, which should be especially helpful for category-focusing examples: Whereas learners with category-avoiding examples have sufficient cognitive resources available to engage in self-explanations, learners with category-focusing examples may suffer from cognitive overload when trying to understand molar solution procedures.

Experiment 1

This preliminary experimental study yielded evidence that category-avoiding examples have the potential to outperform category-focusing examples with regard to later problem solving (details reported in Gerjets, Scheiter, & Kleinbeck, in press). In this study a hypertext-based learning and problem-solving environment (HYPERCOMB, Gerjets, Scheiter, & Tack, 2000) was used for experimentation. HYPERCOMB provided an introduction to probability theory followed by two worked examples for each of the problem categories covered. Participant then had to solve six test problems. To find out whether learners needed to look up example information (e.g., solution formulas) during problem solving we allowed them to re-examine instructional examples in the test phase. Substantial re-examination times might indicate higher memory demands associated with an example format. After having solved the test problems a knowledge test had to be filled in that assessed declarative knowledge concerning probability theory. The same test was administered to assess participants' prior knowledge at the beginning of the experiment.

As a first independent variable, the format of instructional examples was varied between subjects by either providing category-focusing or category-avoiding examples. As a second independent variable, participants were assigned to groups with either high or low prior knowledge. Additionally, transfer distance was varied within subjects by having participants solve three isomorphic and three novel test problems. Isomorphic test problems differed from the instructional examples only with regard to their surface features. Novel test problems were constructed in a way that *two complex-event probabilities* had to be considered whose outcomes had to be multiplied in order to calculate the required probability. An example of a novel test problem is the following tennis problem: "A tennis club has 20 members, 9 women and 11 men, all of them with different last names. For a friendly game against another club a team has to be organized that consists of 2 women and 3 men. The tennis players are chosen by chance. What is the probability of building up a team that consists of Mrs. Miller, Mrs. Jackson, Mr. Byrne, Mr. Thomson and Mr. Myles?"

Performance for solving the test problems and for the declarative knowledge test was recorded. Additionally, example-study time, time spent re-examining examples during problem solving, and problem-solving time were obtained by means of logfile analysis.

Learning with category-avoiding examples led to better problem-solving performance accompanied by less example-study time and less time for re-examining examples during problem solving. This could be shown independently of learners' prior knowledge and of transfer distance. There were no differences between the example-format groups with regard to declarative knowledge acquisition. Similarly, there were no differences in problem-solving time. These findings confirm the expected superiority of the category-avoiding example format with regard to learning demands and subsequent problem-solving performance.

Experiment 2

Experiment 2 was conducted to further explore three issues. First, we wished to obtain direct evidence for the assumption of reduced cognitive load when studying category-avoiding examples. Second, we wanted to test the predicted interaction between example formats and instructional explanations. Third, a possible artifact had to be ruled out: The increased time for re-examining category-focusing examples during problem-solving in Experiment 1 revealed that this example format may impose higher memory demands onto learners. These demands might be responsible for performance impairments because they may interfere with example processing. To rule out this explanation we provided learners in the category-focusing condition of Experiment 2 with formulas as a memory aid during problem solving. The formula list should reduce the memory burden compared to re-examine instructional materials during problem solving (the approach used in Experiment 1).

Method

Participants Participants were 68 students (28 female, 40 male) at the Georgia Institute of Technology who participated for course credit. Average age was 19.6 years.

Materials and procedure A slightly modified version of HYPERCOMB was used for this experiment. Two worked examples were provided for each of the four problem categories taught. After studying these examples participants solved three isomorphic and six novel test problems. Input fields were used to fill in the problem solutions as fractions (e.g., 1/210). Participants were given no opportunity to re-examine instructional examples in the test phase. Instead, formulas were provided during problem solving for those participants who had to apply solution formulas (i.e., those learning with category-focusing examples). After solving the test problems, participants took a knowledge test that assessed declarative knowledge on probability theory. The same test was used to assess participants' prior knowledge at the beginning of the experiment.

Design and dependent measures As a first independent variable the *format of the instructional examples* during the learning phase of HYPERCOMB was varied between subjects. The worked examples were either presented in the category-focusing or the category-avoiding example format. As a second independent variable the *degree of instructional explanations* was varied between subjects. The instructional examples were presented either with instructional explanations that provided detailed justifications for solution steps or the examples were presented in a rather condensed version that focused on the mathematical structure of example solutions without providing instructional explanations (see Table 1). The examples used in Experiment 1 fell in between these two extremes with regard to the degree of instructional explanations. Additionally, *transfer distance* was varied within subjects.

Performance for problem solving and for the declarative knowledge test was recorded. Example-study time, and problem-solving time were obtained by means of logfile analysis. Additionally, different aspects of cognitive load were assessed after the problem-solving phase by administering a modified version of the NASA-TLX (Hart & Staveland, 1988). Each of the three cognitive load items that are described in more detail in the results section was rated on a scale ranging from 0 to 100.

Results

Initially we analyzed participants' prior knowledge (see Table 2) by means of an ANOVA (example format x instructional explanations), which yielded no significant main effects or interactions. Possible performance differences between the experimental conditions can thus be interpreted unambiguously as effects of the instructional materials.

Performance data In order to determine the influence of the three independent variables on problem-solving performance for isomorphic and novel test problems, a MANOVA (example format x instructional explanations x transfer distance) was conducted. As expected, participants who had learned with category-avoiding examples clearly outperformed participants learning with category-focused examples ($F_{(1,64)} = 13.73$; $MS_E = 1204.81$; $p < .001$). There was, however, no effect of instructional explanations nor was there an interaction between the two factors (both *F*s < 1). Additionally, isomorphic problems were easier to solve than novel problems ($F_{(1,64)} = 78.60$; $MS_E = 386.80$; $p < .001$). The interaction between example format and transfer distance failed to reach statistical significance (F(1,64) = 2.56; MSE = 386.80; p < .15). There were no other interactions (all Fs □ 1).

In order to examine the influence of example formats and instructional explanations on the acquisition of declarative knowledge an ANOVA was conducted for performance in the knowledge test. There was a non-significant trend for the category-avoiding example format to foster knowledge acquisition ($F_{(1,64)} = 3.34$; $MS_E = 176.40$; $p < .10$). There were no other significant effects (both *F*s < 1).

Table 2: Results of Experiments 2

Instructional Explanations	**Without**		**With**	
Example format	**Focus**	**Avoid**	**Focus**	**Avoid**
Prior knowledge (in % correct)	54.1	55.6	57.2	55.6
Performance (in % correct)				
- Isomorphic Problems	43.1	70.6	47.1	74.5
- Novel Problems	25.5	35.3	15.7	39.2
- Knowledge Test	64.2	67.9	63.1	71.1
Time measures (in sec)				
- Example study	418	273	659	370
- Problem solving	1514	1334	1524	1354
Cognitive load (in scale values)				
- Task demands	37.4	40.3	40.0	21.2
- Task effort	33.2	31.8	34.7	16.2
- Stress	25.9	15.9	22.1	12.1

Time data A two-factor ANOVA (example format x instructional explanation) was conducted for example-study time as well as for problem-solving time. Not only were participants learning with a category-avoiding example format more successfully with regard to problem-solving performance, but they also needed far less time studying the examples than participants learning with category-focused examples ($F_{(1,64)} = 10.45$; $MS_E = 76560.56$; $p < .001$). Rather naturally, the more instructional explanations were provided to participants the longer they needed to process them ($F_{(1,64)} = 6.35$; $MS_E = 76560.56$; $p < .05$). There was no interaction between the two factors ($F_{(1,64)} = 1.13$; $MS_E = 76560.56$; $p > .25$). With regard to problem-solving time we obtained no main effect for either example format ($F_{(1,64)} = 1.72$; $MS_E = 303501.60$; $p > .15$) or instructional explanations ($F < 1$) nor was there an interaction ($F < 1$).

Cognitive load scales First, with regard to the *task demands* associated with the learning task, both main effects failed to reach statistical significance (example format: $F_{(1,64)} = 2.38$; $MS_E = 450.87$; $p > .10$; instructional explanations: $F_{(1,64)} = 2.56$; $MS_E = 450.87$; $p > .10$). However, a significant interaction ($F_{(1,64)} = 2.38$; $MS_E = 450.87$; $p < .05$) indicated that participants judged the learning task as being less demanding in the category-avoiding example format than in the category-focused format when learning with instructional explanations, whereas there was no difference between the two example formats when no explanations were given. Second, with regard to the *effort* participants believed they had to invest in the task, they indicated that they had to work less hard in order to understand the instructional contents when learning with category-avoiding examples ($F_{(1,64)} = 4.21$; $MS_E = 403.81$; $p < .05$). There was no main effect for instructional explanations ($F_{(1,64)} = 2.10$; $MS_E = 403.81$; $p > .15$). Finally, participants experienced less *stress* during learning with category-avoiding examples ($F_{(1,64)} = 4.96$; $MS_E = 342.65$; $p < .05$) whereas there neither was a main effect of instructional explanations nor an interaction ($F < 1$).

Discussion

In this paper, we provided evidence for abandoning the general idea that worked examples should aim a conveying problem categories and category-specific solution procedures. Instead we propose that it is better to design instructional examples in a way that supports the understanding of relations between structural problem features and individual solution steps, i.e. relations that hold below the category level. This category-avoiding example approach allows one to free up cognitive resources as indicated by our cognitive load results. These cognitive resources can in turn be devoted to profitable processes such as comparing and elaborating examples. Furthermore, the knowledge resulting from studying these types of examples can be more easily adapted to novel problems because of their modularity. The additional provision of instructional explanations was not very helpful in fostering skill acquisition – a finding that fits rather well into the existing literature. We provided empirical evidence for the superiority of category-avoiding examples in the domain of probability word problems. We are aware, however, that the example solutions we used might differ in more ways than just the category-focusing/avoiding dimension. For instance, the category-avoiding example solutions involve a good deal of repetition that might also reduce working-memory load. We plan to explore these differences in greater detail in follow-up work. Additionally, we will investigate how the approach of designing category-avoiding examples (that is based on the idea of conveying more general problem-solving strategies that can be applied irrespective of category membership) can be used within a wider range of well-structured and knowledge-rich domains.

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