Learning from Category-Avoiding Instructional Examples Reduces Cognitive Load and Fosters Cognitive Skill Acquisition

Peter Gerjets
Multimedia and Hypermedia Research Unit, Knowledge Media Research Center
Konrad-Adenauer-Strasse 40, 72072 Tuebingen, Germany
Tel: ++49-7071-979219, Fax: ++49-7071-979100
p.gerjets@iwm-kmrc.de

Katharina Scheiter
Department of Applied Cognitive Psychology and Media Psychology, University of Tuebingen
Konrad-Adenauer-Strasse 40, 72072 Tuebingen, Germany
Tel: ++49-7071-979330, Fax: ++49-7071-979100
k.scheiter@iwm-kmrc.de

Richard Catrambone
School of Psychology, Georgia Institute of Technology
654 Cherry Street, Atlanta, Georgia 30332-0170, USA
Tel: ++1-404-894-2682, Fax: ++1- 404-894-8905
rc7@prism.gatech.edu

Problem-type schemata are often seen as an important prerequisite for skilled problem solving. These schemata represent problem categories together with category-specific solution procedures and can be best acquired by *studying concrete instances* of problem categories (i.e., examples). Usually instructional worked examples are designed in a *molar way* to convey knowledge on problem categories (that are defined by multiple structural problem features) and category-specific solution procedures *(category-focusing examples)*. In contrast, we propose to design instructional examples in a *modular way* that focuses on the understanding of relations between individual structural problem features and individual solution steps, i.e. relations that hold below the category level *(category-avoiding examples)*. We designed instructional examples (see Table 1) in the domain of calculating the probability of complex events (e.g., 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 medal?) Like many other topics, the calculation of complex-event probabilities is usually taught by means of a category-specific solution formula in which multiple steps are collapsed into a single formula that applies to all problems sharing a characteristic pattern of structural features. Studying category-focusing examples requires to consider multiple structural problem features in parallel in order to understand the problem's category membership. Therefore, a substantial *cognitive load* may result depending on the number of relevant structural problem features. Moreover, 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 holding irrespective of category membership such as relations between structural problem features and individual solution steps might be poorly understood. As a result, learners may not learn to relate individual structural problem features to characteristics of the problem solution and thus may fail to adapt solution procedures to novel problems beyond the known problem categories. 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 features across the boundaries of problem categories. Two experiments showed a clear superiority of category-avoiding examples with regard to learning time, cognitive load, and problem-solving performance for isomorphic as well as novel problems compared to traditional category-focusing examples.

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

CATEGORY-FOCUSING EXAMPLE SOLUTION	CATEGORY-AVOIDING EXAMPLE SOLUTION
Problem features: *Selection* of 3 sprinters out of 7, *order* of selection is important; each sprinter can only be selected *once* (*without replacement*)	**Rationale:** Calculate probability of correctly guessing the winner of each medal; each medal can be taken into account *separately*.
Formula: $A = n! / (n-k)!$	**Step 1:** *7* possible choices (sprinters), *1* acceptable (winner): 1/7
Inserting: $n = 7$, $k = 3 \Rightarrow A = 7! / (7-3)! = 210$	**Step 2:** *6* possible choices (winner can't win again), *1* acceptable: 1/6
Result: 1/210	**Additional steps:** Analogous procedure
	Result: *Overall probability*: 1/7 * 1/6 * 1/5 = 1/210