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# A Methodological Alternative to Media Comparison Studies: Linking Information Utilization Strategies and Instructional Approach in Hypermedia Learning

**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

**Peter Gerjets (p.gerjets@iwm-kmrc.de)**

Hypermedia Research Unit, Knowledge Media Research Center  
Konrad-Adenauer-Strasse 40, 72072 Tuebingen, Germany

**Brigitte Vollmann (vollmann\_cmr@gmx.de)**

Center for Media Research, Freie Universität Berlin,  
Malteserstr. 74-100, 12249 Berlin, Germany

**Richard Catrambone (rc7@prism.gatech.edu)**

School of Psychology, Georgia Institute of Technology  
Atlanta, Georgia 30332-0170, USA

## Abstract

Literature reviews on hypermedia learning have yet failed to show consistent positive effects of learner-controlled nonlinear information access. We argue that a possible reason for this lack of evidence in favor of hypermedia learning results from the fact that not sufficient attention is paid to the strategies of information utilization learners deploy. The few studies that do analyze these strategies fail to link them to an instructional approach, which hampers a deeper interpretation of strategy patterns. Our study showed that different groups of learners can be distinguished according to their strategies used in an example-based hypermedia environment and that these groups differ with regard to learning outcomes, but not individual learner characteristics.

## Is Learning with Hypermedia Ineffective?

Hypermedia environments are nonlinear information networks, which can be explored in multiple ways with the learner having control over the selection, sequencing, and pacing of information. Learner control is seen as beneficial for knowledge acquisition for different reasons: First, learners can adapt the presentation of information to their preferences and needs. Second, learner control requires a deeper information processing, because learners have to compare the options offered to come to an informed decision. Third, learner control may train meta-cognitive self-regulation abilities. Fourth, it may improve motivation to learn and learners' attitude towards the topic. Despite these hypothesized advantages, literature reviews have yielded ambiguous results concerning the effectiveness of hypermedia learning over other forms of instruction (Dillon & Gabbard, 1998).

In the remainder of the paper, two arguments will be brought forward and supplemented by some initial empirical support: First, it is proposed that analyzing the way learners make use of information offered in hypermedia environments might be a promising methodological alternative to global media comparisons. Most of the existing studies tend

to ignore that once learner control is provided, learners' information utilization behavior will show an increased variance. Thus, whether hypermedia is effective will depend on whether learners use the available information in a way that knowledge acquisition processes are facilitated.

Second, the analysis of information utilization strategies should be linked to the instructional approach implemented in a hypermedia environment. Based on cognitive task analyses and empirical evidence, an instructional approach (e.g., learning from worked-out examples) can be characterized by a set of cognitive processes (e.g., example elaborations and comparisons) that enable knowledge acquisition (e.g., construction of a problem schema), where different cognitive processes require different information as input. Thus, an effective information utilization strategy can be defined *a priori* by the fact that information is selected, sequenced, and paced in a way that cognitive processes relevant to the instructional approach are facilitated.

Until now, there are only a few studies that have considered strategies of information utilization when studying hypermedia learning. Barab, Bowdish, Young, and Owen (1996) used students' navigational profiles based on different strategy indicators (e.g., number of pages retrieved, depth of search) to predict whether a user had been given a specific information search goal for browsing the system. Balcytiene (1999) identified different groups of learners (i.e., self-regulated learners, cue-dependent learners) by means of logfile and video analyses for her hypertext system on gothic architecture. Cue-dependent learners did not browse the environment in a systematic way and oriented themselves towards its local aspects, while self-regulated learners reflected on the accessed information and were oriented towards the global structure of the system. In accordance with this interpretation of the navigational profiles and video data, the posttest revealed superior retention for self-regulated learners. Lawless and Kulikowich (1996) used a cluster-analytical approach to identify different

groups of users (i.e., knowledge seekers, feature explorers, and apathetic users), which were then compared with regard to different external criteria. Knowledge seekers, who had used the information most intensively, had a higher prior knowledge and showed better learning outcomes than the other groups. The authors conclude that “the navigational strategies employed by the ‘knowledge seekers’ are the most like the sophisticated reading strategies used by competent traditional text processors” (p. 395f.). Moreover, apathetic users may lack the prior knowledge necessary to deploy effective information utilization strategies.

The aforementioned studies take a first step into the right direction by focusing on users’ information utilization strategies. However, their interpretation of learners’ navigational profiles is done in a post-hoc way without linking them to the instructional approach implemented in the hypermedia environment (if there is one approach to begin with). In the next section, we illustrate how an analysis of information utilization strategies can be based on an instructional approach and its underlying cognitive processes.

### **Defining Information Utilization Strategies for an Example-based Hypermedia Environment**

For our study we chose the instructional approach of example-based learning to illustrate the claim that research on hypermedia learning can be improved by analyzing learners’ strategies of information utilization in terms of the instructional approach implemented in the hypermedia system: The advantage of choosing example-based learning is that there are already many findings on cognitive strategies supporting this instructional approach – many of them being based on cognitive load theory (CLT, Sweller, 1999).

The CLT is an instructional design theory that specifies helpful conditions for cognitive skill acquisition. These skills are assumed to be represented as problem schemas. Many of the instructional settings analyzed on the basis of cognitive load theory involve the use of worked-out examples for conveying problem schemas, as examples have been shown to be very successful for this purpose at least for novice learners (cf. Atkinson, Derry, Renkl, & Wortham, 2000). CLT assumes a direct causal relationship between a specific instructional design, cognitive activities, the resulting pattern of cognitive load, and the learning outcomes is assumed. Recently, Gerjets and colleagues (Gerjets & Hesse, 2004; Gerjets & Scheiter, 2003) have extended the CLT so that it can be used to analyze learner-controlled settings, where learners can select among different strategies of handling the instructional materials. In the augmented CLT, it is thus proposed that whether an instructional design results in either helpful or harming cognitive load depends on learners’ strategies of information utilization. Moreover, learner characteristics are included as factors that may influence strategy selection. The augmented CLT may thus serve as a framework for analyzing information utilization strategies in example-based hypermedia environments.

From a cognitive load perspective, effective information utilization strategies with respect to examples consist in

selecting examples that facilitate cognitive processes relevant to the acquisition of problem schemas. Examples that support schema acquisition have the following characteristics: First, effective examples reduce the intrinsic load inherent to the domain (cf. Gerjets, Scheiter, & Catrambone, 2004). Second, examples that foster schema acquisition keep extraneous cognitive load, which results from cognitive processes not relevant to learning, at a minimum. Third, they facilitate higher-level cognitive processes that go beyond the mere activation of information in working memory, and that result in germane cognitive load. These processes consist in example elaborations and comparisons. Elaborations occur when learners draw inferences concerning the structure of example solutions, the rationale behind solution procedures, and the goals that are accomplished by individual solution steps (i.e., self-explanations, Renkl, 1997). Beyond self-explanations, learners should engage in example comparisons in order to notice structural features that differ among problem categories and that are shared by problems within a category (Quilici & Mayer, 1996).

Based on these characteristics, four groups of example utilization strategies were identified: Learners should retrieve examples that (1) result in low intrinsic cognitive load, (2) support processes of comparison (3) stimulate self-explanations, (3) and compensate for lacking self-explanations. In the following, these strategies will be illustrated in the domain of probability theory, where extensive research has been done on the differential effectiveness of different example formats in system-controlled settings. In the hypermedia environment used in the study all these example formats were included and learners could select among formats that had been proven either effective or non-effective in the prior system-controlled studies.

### **Low Levels of Intrinsic Cognitive Load**

A low intrinsic cognitive load has been found for *modular* rather than *molar* examples (Gerjets et al., 2004; Gerjets, Scheiter, & Catrambone, 2006). Molar examples have a recipe-like structure and refer to complex entities like problem categories, clusters of structural task features, and category-specific solution procedures. In modular examples, solution procedures are broken down into smaller meaningful groups of solution steps that can be understood in isolation. They require learners to keep only a limited number of elements active simultaneously in working memory. Evidence for the superiority of modular examples was found in terms of learning time, self-reported cognitive load, and later problem-solving performance for isomorphic and novel problems (Gerjets et al., 2004, 2006). Accordingly, an effective example utilization strategy consists in preferring modular over molar examples.

### **Supporting Example Comparisons**

Comparing examples with different surface features within problem categories and comparing examples with similar surface features across categories are both helpful cognitive processes to identify the relevant structural problem features

of problem categories (Scheiter & Gerjets, 2005). Comparing examples with different surface features within categories may help to identify varying features, which must be irrelevant for category membership, while commonalities may indicate structural features. On the other hand, comparing examples with the same surface features across problem categories may highlight structural differences among the examples. In general, differences among instances become more salient, the more other features are shared by them. Thus, for comparisons examples should be selected that differ with regard to only a few features, which can then be identified and interpreted more easily.

### Stimulating Self-explanations

Self-explanations are an important aspect of meaningfully processing examples although they seldom occur spontaneously (Renkl, 1997). Self-explanations can be fostered by presenting *incomplete examples* whose gaps need to be filled in (Paas, 1992), by presenting *prompts* that ask learners to generate self-explanations (Berthold & Renkl, 2005), or by a *combination of both methods* (Atkinson, Renkl, & Merrill, 2003). However, in our own studies we could not find any beneficial effects of prompting learners to give an explanation for why a specific step to solve a probability problem had been selected (Gerjets et al., 2006). In fact, while self-explanation prompts did not affect learning from molar examples, they even hindered learning from modular examples. We explained these results by assuming that learners in the modular-examples condition were forced to generate self-explanations for material that they had already sufficiently understood and that was thus redundant to them. Accordingly, one might argue that at least for those learners who have already understood the principles illustrated, an effective example utilization strategy might consist in *not* retrieving examples that contain self-explanation prompts. On the other hand, it might well be that if learners can decide by themselves whether to select these examples, only learners who need processing support will retrieve them.

### Compensating for Lacking Self-explanations

Students often overestimate their understanding of examples and thus refrain from further elaborating them. Moreover, even if they have noticed gaps in their knowledge, they may not be able to generate self-explanations to overcome those gaps. These problems may be solved by providing additional *instructional explanations*, particularly for learners with low prior knowledge. Doing so can show learners that they suffer from an illusion of understanding and may help them to overcome comprehension difficulties. Thus, an effective example utilization strategy for novices would be to retrieve examples with instructional explanations. However, as explanations sometimes do not affect learning (Gerjets et al., 2006) or are even harmful because they hinder learners in generating explanations by themselves (Aleven & Koedinger, 2000), learners should retrieve them only if they cannot produce explanations by themselves.

To conclude, effective example utilization strategies con-

sist in retrieving modular examples, in comparing examples that differ only in a few, but relevant features, and in finding the right balance between using examples with or without self-explanation prompts and explanations depending on their level of understanding. This also implies that *strategy patterns* should be analyzed rather than investigating the effects of single strategy variables in isolation. This is why a cluster-analytical approach was preferred over conducting correlational analyses.

## Study

### Method

**Participants.** Seventy-six students of the University of Tuebingen, Germany, were paid to participate in the study. Average age was 25.0 years (32 male, 44 female).

**Materials and Procedure.** We used a hypermedia environment that taught learners how to calculate the probability of complex events. It consisted of an example-based learning phase, and a test phase with problem-solving tasks, and a declarative knowledge test. In the learning phase, each of four problem categories was explained by two worked examples, which differed with regard to their cover story: Always one example dealt with selecting marbles from an urn, while the other was related to daily-life situations. Thus, the same surface features were used across categories for the urn examples, but varied for the daily-life examples.

To access an example, learners first had to select one of the problem statements from the left navigation bar (Figure 1). The problem statement was then displayed on the format-selection page together with eight links that allowed retrieving different formats for the presentation of the solution procedure. These formats varied with regard to the solution approach by offering either molar or modular structured solution procedures and with regard to the degree of elaboration and completeness of examples.

Select a format  
for the first urn example

On this page you have to select the format in which the solution to the following example problem is presented to you by clicking the respective link in the table below.

An urn contains five marbles, each a different color - white, yellow, red, green, and blue. Two marbles are taken out, one by one, and are not put back. What is the probability of first taking out the blue marble, and then the white marble?

| formula-based approach                            | individual-event probability approach             |
|---|---|
| <a href="#">solution with elaborations</a>        | <a href="#">solution with elaborations</a>        |
| <a href="#">solution without elaborations</a>     | <a href="#">solution without elaborations</a>     |
| <a href="#">condensed solution</a>                | <a href="#">condensed solution</a>                |
| <a href="#">incomplete examples with feedback</a> | <a href="#">incomplete examples with feedback</a> |

The solution to the example problem may either be stated by using the **formula-based** or the **individual-event probability approach**. Furthermore, it can contain **elaborations** with regard to relevant aspects of the problem, or it can contain **no elaborations**, or the solution can be stated in a very **condensed** way. Please click here for more [information on the alternative solution formats](#).

You may choose to view more than one format for each example in order to receive an illustration of the example's solution in that format.

Figure 1: The format-selection page

Highly-elaborated examples provided detailed explanations for why a solution step had been chosen. Medium-elaborated examples mentioned facts concerning the solu-

tion steps, but no further explanations were given, while in low-elaborated examples only the mathematical information was given. Moreover, incomplete examples with self-explanation prompts / feedback could be selected. Here the solution procedure was medium elaborated and learners were prompted to provide the missing explanations by themselves. After they had typed in the explanation, a feedback page appeared, which contained the learner's response and the system-provided expert explanation. This procedure had to be repeated until explanations had been given for all solution steps; only then another example could be selected. In total, learners could choose among 64 options (i.e., 8 problem statements x 8 solution formats). All participants received the same options to retrieve examples. Learners could decide on their own when to enter the test phase.

**Analyses and Measures.** The analyses consisted in three steps: First, the students' example utilization strategies were subjected to a cluster analysis to identify learner groups with distinct strategies. Second, the relationship between group membership and learning outcomes was investigated. Third, it was tested whether the groups differed with regard to individual learner characteristics.

The variables used to describe *example utilization strategies* were the overall example study time, the overall frequency of retrieving examples, the frequency of retrieving either modular or molar examples as well as the frequency of retrieving either highly-elaborated, medium-elaborated, low-elaborated or incomplete examples. Moreover, we assessed the time spent on the format-selection page as a potential indicator for meta-cognitive awareness. Beyond these measures for the selection and pacing of information, sequencing activities were registered by Markov-chain analyses. The resulting variables comprised the number of transitions between the examples' cover stories, the average number of dimensions changed within a transition from one example to another (e.g., '1' for only changing the degree of elaboration vs. '4' for changing the cover story, solution approach, degree of elaboration, and the category in parallel), and the number of transitions between the molar and modular solution approach. These variables were supposed to provide information on learners' comparison strategies.

The dependent measures consisted in overall *performance* for solving three isomorphic and six novel problems and in the declarative knowledge test. For each of the nine test problems as well as for the eleven items of the declarative posttest one point was assigned for a correct answer; no partial credit was given. Moreover, we assessed *individual learner characteristics*, which were expected to be associated with strategy selection. These included a questionnaire on cognitive and meta-cognitive strategies in mathematics (Wolters, 2004), the Epistemological Beliefs Instrument (Jacobson & Jehng, 1999), the Attitudes Towards Mathematics Inventory (Tapia & Marsh, 2004) and items to assess the preference for amount of instruction (Hannafin & Sullivan, 1996). The original questionnaires were slightly modified and shortened in order not to overwhelm students. Prior

knowledge was assessed by domain-unspecific and specific indicators (i.e., final high school grade, math grade, and performance in a declarative pretest, which was the same as the declarative posttest).

## Results

To identify groups of learners that differ in their example utilization strategies, a cluster analysis (based on the Ward algorithm) was performed on the strategy variables. The so called 'elbow-criterion' was used to stop the clustering process after four clusters had been identified. A three-clusters solution would have increased the within-group variance for the new cluster substantially and thus would have resulted in a loss of information.

For the four-clusters solution, the groups of learners differed significantly in their example utilization strategies (with the exception of 'number of transitions between the cover stories' and 'number of dimensions changed within one transition', cf. Table 1). Cluster 1 – called the *unreflective-intermediate example users* – spent less time on selecting examples than students of Clusters 3 and 4. They studied the selected examples more intensively than students in Clusters 2 and 3, but less than students in Cluster 4. The longer overall example time was the only variable that distinguished between Cluster 1 and 2. Cluster 2 – the *unreflective-lazy example users* – did invest less time on reflecting on the appropriateness of the different formats for displaying the solution procedure and on processing examples than any of the other clusters. Moreover, students in Cluster 2 refrained from switching between modular and molar examples compared to students in Clusters 3 and 4 and did not control for possible illusions of understanding compared to Cluster 4 students. Cluster 3 – the *reflective-sparse example users* – seemed to make well thought-over decisions regarding the solution procedure's format. Learners in this group processed an intermediate number of examples comparable to that of students in Cluster 1, but used less time to study them. Cluster 4 – the *excessive example users* – spent less time on the format-selection page than students of Cluster 3, but retrieved the most examples, which were moreover extensively processed. In particular, they differed from the other groups in their frequent use of molar and of incomplete examples.

In a second step, problem-solving performance and performance in the declarative knowledge test were analyzed by an ANOVA using group membership as a between-subjects factor. Unreflective-intermediate example users and unreflective-lazy example users both performed poorly in the problem-solving task, while reflective-sparse example users and excessive example users performed rather well. These differences across the four groups were significant ( $F(3,72) = 5.13; p < .01$ ), while post-hoc comparisons highlighted differences between Clusters 1 and 3, and Clusters 2 and 3, respectively. Conducting the same ANOVA for the declarative knowledge test revealed slightly different results ( $F(3,72) = 3.72; p < .05$ ). Unreflective-intermediate example

Table 1: Example utilization and performance in the four clusters

|                        | Means            |                  |                  |                 | Results of the post-hoc Tukey tests |                |                |                |                |                |    |
|------------------------|------------------|------------------|------------------|-----------------|-------------------------------------|----------------|----------------|----------------|----------------|----------------|----|
|                        | CL 1<br>(n = 21) | CL 2<br>(n = 12) | CL 3<br>(n = 34) | CL 4<br>(n = 9) | CL 1 -<br>CL 2                      | CL 1 -<br>CL 3 | CL 1 -<br>CL 4 | CL 2 -<br>CL 3 | CL 2 -<br>CL 4 | CL 3 -<br>CL 4 |    |
| <i>Time (sec)</i>      |                  |                  |                  |                 |                                     |                |                |                |                |                |    |
| Format selection       | **               | 1.95             | 1.83             | 8.30            | 5.33                                | ns             | **             | *              | **             | *              | *  |
| Overall                | **               | 11.12            | 3.20             | 8.02            | 25.89                               | **             | **             | **             | **             | **             | ** |
| <i>Frequencies</i>     |                  |                  |                  |                 |                                     |                |                |                |                |                |    |
| Overall                | **               | 15.00            | 10.33            | 19.24           | 31.11                               | ns             | ns             | **             | **             | **             | ** |
| Molar                  | **               | 7.62             | 4.50             | 8.91            | 16.56                               | ns             | ns             | **             | ns             | **             | ** |
| Modular                | *                | 6.62             | 5.67             | 9.88            | 13.44                               | ns             | ns             | ns             | ns             | (*)            | ns |
| Highly-elab.           | *                | 8.38             | 3.00             | 7.00            | 10.89                               | ns             | ns             | ns             | ns             | *              | ns |
| Medium-elab.           | **               | 1.90             | 1.00             | 5.15            | 7.44                                | ns             | (*)            | *              | (*)            | *              | ns |
| Low-elab.              | *                | 1.57             | 5.75             | 5.68            | 6.22                                | ns             | *              | ns             | ns             | ns             | ns |
| Incomplete             | *                | 3.14             | 0.58             | 1.41            | 6.56                                | ns             | ns             | ns             | ns             | **             | ** |
| <i>Transitions</i>     |                  |                  |                  |                 |                                     |                |                |                |                |                |    |
| Cover story            | ns               | 1.48             | 1.42             | 1.41            | 1.44                                | ns             | ns             | ns             | ns             | ns             | ns |
| Dimensions             | ns               | 1.53             | 1.58             | 1.50            | 1.45                                | ns             | ns             | ns             | ns             | ns             | ns |
| Approach               | *                | 2.33             | 1.00             | 6.18            | 9.56                                | ns             | *              | **             | *              | **             | ns |
| <i>Performance (%)</i> |                  |                  |                  |                 |                                     |                |                |                |                |                |    |
| Problem-solving        |                  | 29.87            | 25.67            | 50.80           | 48.48                               | ns             | *              | ns             | *              | ns             | ns |
| Declarative knowledge  |                  | 76.19            | 84.09            | 86.10           | 98.90                               | ns             | *              | *              | ns             | ns             | ns |
| High school grade      |                  | 2.29             | 2.28             | 1.87            | 2.20                                | ns             | *              | ns             | ns             | ns             | ns |

Note: ns = not significant; \*\* =  $p \leq .01$ ; \* =  $p \leq .05$ ; (\*) =  $p \leq .10$ .

users achieved 76.19% correct in the test, which was less than for the reflective-sparse and excessive example users. There were no other differences among the groups. Contrary to our expectations, there were no differences between the four groups with regard to individual learner characteristics with the exception of the final high school grade ( $F(3,72) = 3.02$ ;  $p < .05$ ). Reflective-sparse example users had better high school grades than unreflective-intermediate example users.

### Summary and Discussion

We were able to demonstrate that the analysis of information utilization strategies that have been defined with respect to a specific instructional approach implemented in a hypermedia learning environment helps to identify groups of learners with distinct strategy patterns. These strategy patterns can account for differences in subsequent problem-solving performance as well as in declarative knowledge acquisition. Interestingly, more than one effective strategy pattern could be identified: First, an excessive example utilization proved to be successful, even though these students preferred examples with a high intrinsic cognitive load (i.e., molar examples). One possible explanation for the latter might be that these students at the same time most frequently monitored their understanding by selecting incomplete examples. Thus, they might not have chosen the most efficient strategy – which would have been to focus on modular examples – but compensated for that by a very thorough example processing. Second, learners also performed well when using examples only sparingly. In the

latter case, the display format for the solution procedure seemed to have been rather carefully selected as indicated by the time spent on the format-selection page. Thus, studying only a few examples can be an effective strategy as long as one invests more thinking on selecting the most suitable examples (i.e., meta-cognitive effort). Moreover, the time spent on the format-selection page might also be interpreted as a learner’s attempt to reason about a possible solution to the problem, before looking at a specific solution procedure (cf. anticipative reasoning, Renkl, 1997). Interestingly, learners with this example utilization strategy had better average high school grades than at least one of the other groups. This might indicate better general abilities that help to regulate one’s learning activities in an efficient way. Contrary to results by Renkl (1997) or Lawless and Kulikowich (1997), learners with this efficient, but probably knowledge-rich strategy formed a large group in our sample.

While the pacing and selection variables were suited to distinguish among different behavioral patterns, the sequencing variables only accounted for a small part of the variance. These variables were problematic, because they were defined at a very coarse level making it hard to interpret them unambiguously. For instance, looking only at examples from different problem categories embedded in the same cover story might be as effective as repeatedly comparing examples within a problem category embedded into different cover stories – both strategies resulting in completely different values for the respective variable. Thus, in the future a more fine-grained definition and analysis of sequencing strategies needs to be deployed.

Unfortunately, although we assessed a variety of learner characteristics, we could not identify characteristics that differentiated between different example utilization groups. We used constructs that have been identified as being relevant to learner-controlled instruction in the literature from a theoretical perspective and we selected the most reliable measures available to assess these constructs. Thus, there might be something wrong with questionnaires that assess cognitive and meta-cognitive knowledge and attitudes in general. Accordingly, Winne, Jamieson, and Muis (2001) have suggested using unintrusive data like logfiles not only to analyze strategic behavior, but also to interpret this data as indicators for meta-cognitive abilities. Moreover, most of the questionnaires that have been used to predict behavior in learner-controlled settings assess global cognitive and meta-cognitive abilities rather than domain-specific ones.

Beyond these methodological difficulties, analyzing the way learners make use of the information provided seems to be a more fruitful approach to investigating hypermedia than global media comparisons. The latter fail to consider the specific characteristics of the media and thus produce ambiguous results. Analyses of learners' information utilization may furthermore help to improve instruction by informing the design of strategy prompts and trainings to support students in learning with hypermedia.

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