

# The impact of learner characteristics on information utilization strategies, cognitive load experienced, and performance in hypermedia learning

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## Abstract

Against the background of an adaptation of Cognitive Load Theory to learner-controlled settings we investigated the impact of learner characteristics on information utilization strategies, cognitive load, and learning outcomes in a hypermedia environment. Based on the data of 79 students, five clusters of students were identified according to their learner characteristics by means of a cluster analysis. Further analyses showed that learners with more favorable characteristics (i.e., higher prior knowledge, more complex epistemological beliefs, more positive attitudes towards mathematics, better cognitive and metacognitive strategy use) tended to show a more adaptive example utilization behavior, reported less cognitive load, and solved more problems correctly than learners with less favorable characteristics.

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## 1. Introduction

Hypermedia learning comprises a high level of interactivity, where students may decide on the order of information, the to-be-retrieved content and on its display format. This learner control is seen as the major advantage for learning, because it supposedly facilitates the active construction of flexible knowledge structures (Jacobson & Spiro, 1995). However, respective literature reviews fail to show that hypermedia supports interactive knowledge construction (Dillon & Gabard, 1998). To make hypermedia learning more effective, Dillon and Jobst (2005) recently proposed applying instructional-design theories like the Cognitive Theory of Multimedia Learning (CTML; Mayer, 2005) or the Cognitive Load Theory (CLT; Sweller, van Merriënboer, & Paas, 1998) to hypermedia. Both theories argue that humans' information processing capacities are limited with regard to the amount of information that they can handle in parallel in working memory. Thus,

instructional design should reduce processing demands irrelevant to learning and thereby free cognitive resources for sense-making knowledge-construction activities. At this general level, this guideline is applicable to every instructional setting irrespective of whether it is controlled by the system or by the learner. However, from a theoretical perspective both theories are more in accordance with system-controlled instruction, where learners are presented with predefined contents displayed in a specific representational format to-be-studied in a fixed order and which constrains the range of observable and cognitive learner activities. Thus, a one-to-one mapping of instructional design and cognitive activities is assumed in that "a given instructional design will elicit the same specific learner activities for all learners" (Van Gog, 2006, p. 22).

In learner-controlled settings, however, students may assemble different information diets. For instance, one learner may decide to study only animations, whereas another reads text only. CTML and CLT assume that these representational formats are associated with different cognitive activities and patterns of cognitive load, which in turn determine learning outcomes. Thus, although the two learners have studied within

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the same learning environment, they will not necessarily experience the same pattern of cognitive load or show similar learning outcomes due to the fact that they have decided on different information diets eliciting different cognitive activities (one-to-many mapping). Accordingly, Gerjets and colleagues (Gerjets & Hesse, 2004; Gerjets & Scheiter, 2003) have proposed that in learner-controlled instructional settings the relation between instructional design and cognitive load becomes less deterministic, as it is moderated by the way learners make use of the information offered to them during interactive knowledge construction.

A major question in hypermedia research has been from where the aforementioned variability in information utilization strategies emerges. There is converging evidence that learner characteristics moderate the way in which the students process hypermedia environments and, thus, how they succeed in interactive knowledge construction. These complex relationships among learner characteristics, information utilization strategies, cognitive load, and learning outcomes are captured in the augmented CLT model suggested by Gerjets and colleagues (Gerjets & Hesse, 2004; Gerjets & Scheiter, 2003), which is thus used as a framework for the present study.

### 1.1. The role of learner characteristics

Learner characteristics have been shown to moderate instructional effectiveness in a wide range of instructional settings since the discovery of so-called aptitude–treatment–interactions (Cronbach & Snow, 1977). Nevertheless, they have their strongest impact in learner-controlled settings as was demonstrated in research by Young (1996) or by Schwartz, Anderson, Hong, Howard, and McGee (2004), for instance. The present study focused on investigating multiple learner characteristics in parallel, whose impact has either been substantiated theoretically or empirically in prior research. A multivariate approach was chosen to assess the degree of interplay that may exist among multiple characteristics.

There is consistent evidence that students with high levels of *prior knowledge* apply deeper processing strategies, require less instructional support, and produce better learning outcomes when learning with hypermedia (for a review see Chen, Fan, & Macredie, 2006). Prior knowledge guides information selection, whereby students with high prior knowledge are better able to identify their knowledge needs and make their selections accordingly (Gall & Hannafin, 1994; Lawless & Kulikowich, 1996; MacGregor, 1999). While the impact of prior knowledge on hypermedia effectiveness is well established, it is interesting to investigate whether other learner characteristics may account for additional variability. Possible candidates comprise students' self-regulatory skills, preferences for amounts of instruction, and epistemological beliefs.

Hypermedia has been shown to be more effective for learners with good *self-regulatory skills*, which include cognitive and metacognitive, motivational and emotional, as well as behavioral processes that result in active learning

(Azevedo, 2005). Metacognitive skills refer to learners' abilities to set goals, determine the information that is suited to achieve those goals, and to monitor progress towards these goals; they can be seen as a necessary prerequisite to exercise control over instruction. Motivational and emotional processes are often linked to students' attitudes towards a learning domain in that students with a positive attitude are more motivated, value the topic, feel enjoyment when dealing with it, and are sufficiently confident regarding their skills in the domain (Tapia & Marsh, 2004). As a consequence for learning, students with more positive attitudes show a higher engagement in the task and invest more resources into learning (e. g., time; Lawless & Kulikowich, 1996). The latter may be moreover affected by students' *preferences for amount of instruction*, whereby students with a preference for receiving larger amounts of instruction are more successful in learner-controlled settings (Hannafin & Sullivan, 1996).

Finally, students with more complex *epistemological beliefs* have been shown to perform better in hypermedia learning than those with more simplistic beliefs (Bendixen & Hartley, 2003; Jacobson, Maouri, Mishra, & Kolar, 1995; Jacobson & Spiro, 1995). This multidimensional construct refers to the conceptions that learners have with regard to knowledge and its acquisition. For instance, students with naïve epistemological beliefs tend to believe that absolute knowledge exists and will eventually be known, knowledge acquisition occurs as an orderly process, or that learning occurs either in a quick or all-or-none fashion (cf. Schraw, 2001). To explain how epistemological beliefs affect hypermedia learning it is assumed that students with more complex beliefs are more willing to invest mental effort in comparing and contrasting different sources of information, reflecting on the validity of information, and in finding as much information as possible to satisfy their learning goals (Bendixen & Hartley, 2003; Jacobson & Spiro, 1995). A heated discussion in the literature on epistemological beliefs focuses on their dual nature with regard to whether they are domain-specific or not. More recent research suggests that both – domain-general and domain-specific beliefs – exist in parallel and influence each other. A recent study by Schommer-Aikins, Duell, and Hutter (2005) showed that both types of beliefs were highly correlated to each other and that both were able to predict middle school students' academic performance in mathematics. Buehl and Alexander (2005) conclude that domain-specific epistemological beliefs may emerge in more precise situations; however, they are developed from more general beliefs and are thus highly connected to them. Thus, while being aware of this ongoing discussion, in the present study it was decided to assess epistemological beliefs as a domain-general construct, thereby also owing to the fact that it was aimed at being able to compare results to prior studies, where epistemological beliefs had been assessed at a general level (Bendixen & Hartley, 2003; Jacobson et al., 1995).

To conclude, the aforementioned learner characteristics are very likely to affect interactive knowledge construction in hypermedia environments. They do so by influencing a learner's information utilization strategies (e.g., comparing

information, processing information more extensively etc.) in that learners with a higher level of prior knowledge, good self-regulatory skills, high preferences for amount of instruction, as well as more sophisticated epistemological beliefs are assumed to deploy more effective strategies than learners with different characteristics. Hence, strategies are assumed to mediate the relationship between learner characteristics and learning outcomes (Hartley, 2001; Scheiter & Gerjets, 2007). To predict how effective information utilization strategies might look like, these will be conceptualized against the background of a specific instructional approach in the following (i.e., example-based learning).

### 1.2. Information utilization strategies and instructional approaches

Several studies have shown that learners can be distinguished according to their navigational profiles and that different navigational profiles are associated with differences in learning outcomes (Barab, Bowdish, & Lawless, 1997; Lawless & Kulikowich, 1996; MacGregor, 1999). The emerging picture is that students who are using an either passive or an active-but-superficial approach to navigating hypermedia environments score low on learning outcome measures, whereas an active-and-thorough approach results in favorable learning outcomes. The apparent superficiality of this statement is caused by the fact that there is no common way of describing and interpreting information utilization across different studies; rather, what constitutes a thorough approach solely depends on the hypermedia environment investigated. As a solution to this problem, several authors (Jacobson & Spiro, 1995; Scheiter & Gerjets, 2007) have proposed to link information utilization strategies to the specific instructional approach implemented in the hypermedia environment and to interpret strategies in reference to this instructional approach. Following this suggestion, in the present study, hypermedia research was combined with cognitive task analyses to determine successful processing strategies and with insights on the acquisition of problem schemas from worked-out examples, as this was the learning approach that was implemented in the hypermedia environment.

Example-based learning can be characterized by a set of cognitive processes that enable the acquisition of problem-solving skills, where different cognitive processes require different information as input. From a cognitive load perspective (Sweller et al., 1998), effective example utilization strategies consist in using examples that facilitate cognitive processes relevant for the acquisition of problem schemas by improving the ratio of intrinsic, extraneous, and germane cognitive load. In the following, four groups of example utilization strategies will be introduced that comply with this general cognitive load argumentation. Prior to the present study, several system-controlled studies were conducted in the domain of probability theory by the authors, where the example formats described in the subsequent sections were compared to each other to determine their effectiveness. In the present study, all these example formats were made available in a hypermedia environment.

At this point, it is important to not to confuse two types of meaning that may be associated with the term “strategy”. *Strategies of information/example utilization* refer to the observable selection behavior in the hypermedia environment that can be made accessible through logfiles (i.e., how often is a specific example format retrieved and for how long is it studied by a learner?). These strategies are assumed to be moderated by learner characteristics (e.g., a learner with a high level of prior knowledge selecting more examples of type A than of type B). At the same time, each of the example formats offered in the hypermedia environment enables and facilitates specific cognitive processes like self-explanations or comparisons, that is, *strategies of learning from examples*. The latter strategies are linked to the design of the examples. Hence, it is assumed that a learner deploys a specific example utilization strategy by selecting an example format for further processing. By selecting this example, s/he can now apply strategies of learning from examples that are more likely to occur with this example format and that would be less likely if a different example format had been chosen initially. This distinction between two levels of strategy application is very alike to that of Kennedy (2004), who distinguishes between functional interactivity at a behavioral level and cognitive interactivity in his model on interactivity in multimedia research. Both types of interactivity are assumed to influence each other in that functional interactivity enables cognitive interactivity, whereby the latter in turn influences the prior (e.g., the wish to compare examples requires the selection of another example).

To conclude, an effective example utilization strategy is characterized by the fact that examples are chosen that facilitate the application of helpful strategies of learning from examples. The latter strategies are discussed in the following.

#### 1.2.1. Example formats with low intrinsic cognitive load

In a number of studies we analyzed the effectiveness of modular and molar examples for teaching students how to calculate complex-event probabilities (Gerjets, Scheiter, & Catrambone, 2006). Molar examples (see Fig. 1a) 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 solution steps. They require learners to keep only a limited number of elements active in working memory, thereby abating intrinsic cognitive load. Modular examples (see Fig. 1b) reduce learning time and self-reported cognitive load, as well as improve problem-solving performance for isomorphic and novel problems (Gerjets et al., 2006). Accordingly, an effective example utilization strategy consists in preferring modular to molar examples.

#### 1.2.2. Examples that compensate for lacking self-explanations

Effective examples will facilitate higher-level cognitive processes (e.g., elaborations) and thereby increase germane cognitive load. Elaborations occur when learners draw

**a**

**100m-sprint example:  
Permutation without replacement**

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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?

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**Identify task features:** The given 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. Therefore, this problem is a problem "without replacement". That is, after a sprinter wins a medal he is not eligible for being selected again.

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**Apply formula:** For this type of problem the following formula should be applied:

$$A = \frac{n!}{(n - k)!}$$

with  $n$  being the number of all participants in the 100m-sprint and  $k$  being the number of sprinters that have to be correctly guessed.

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**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 the group of 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.

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**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  $1/210$ .

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**b**

**100m-sprint example**

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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?

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**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  $1/7$ .

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**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  $1/6$ .

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**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  $1/5$ .

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**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  $1/7 * 1/6 * 1/5 = 1/210$ .

Fig. 1. (a) Molar example formats. (b) Modular example formats.

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, 2002). However, 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 (Renkl, 2002). Thus, an effective example utilization strategy for novices would be to retrieve examples that contain additional instructional explanations. However, as explanations sometimes do not affect learning or are even harmful because they hinder learners in generating explanations themselves (Gerjets

et al., 2006), learners should retrieve them only if they cannot produce explanations themselves. Similarly, Renkl (2002) suggests to provide as few instructional explanations as necessary and to stimulate as many self-explanations as possible.

### 1.2.3. Examples that stimulate self-explanations

Self-explanations can be fostered by incomplete examples whose gaps need to be filled in (Paas, 1992) or by prompting learners to generate self-explanations (Atkinson, Renkl, & Merrill, 2003). Therefore, selecting incomplete examples or examples with self-explanation prompts may be an effective strategy for increasing germane cognitive load. However, when combining self-explanation prompts with modular examples it was found that self-explanation prompts hindered

learning (Gerjets et al., 2006). A possible explanation for these results is that the learners had already sufficiently understood the principles when studying worked examples without prompts, before being asked to generate explanations for a second problem. Thus, they were prompted to elaborate information that was redundant to them (cf. expertise reversal effect; Kalyuga, Ayres, Chandler, & Sweller, 2003). Accordingly, for knowledgeable learners an ineffective example utilization strategy might consist in retrieving examples that contain self-explanation prompts, because it increases extraneous cognitive load.

#### 1.2.4. Example combinations that support comparisons

Beyond self-explanations, learners should engage in example comparisons as a means of increasing germane cognitive load. Comparing examples that are embedded in different cover stories, but belong to the same problem category may help learners to discover that these varying features of the cover story are irrelevant to the solution of the problem, because if they were not, different solution procedures would be required for each problem. On the other hand, commonalities of examples within a problem category may indicate structural features. The same conclusion can be drawn from comparing examples with similar cover stories across problem categories, where despite these similar surface features different solution procedures are required, thereby hinting to the irrelevance of these features and highlighting structural differences among the examples. Both types of comparisons are helpful to identify the relevant structural features of problem categories (Cummins, 1992; Quilici & Mayer, 1996; Scheiter & Gerjets, 2005). Thus, examples should be selected that facilitate these comparisons, either because they vary cover stories within problem categories or because they keep the cover story constant across categories.

#### 1.3. The present study – hypotheses

Students were first distinguished according to their learner characteristics by means of a cluster analysis. It was expected that there would be distinct clusters, whose profiles are not determined only by differences in prior knowledge, but also by differences in self-regulation abilities, preferences for amount of instruction, and epistemological beliefs (Hypothesis 1). Second, it was analyzed how these profiles of learner characteristics would affect strategies of using different example formats in a hypermedia environment, the experienced cognitive load, and problem-solving performance. In line with the prior research (Azevedo, 2005; Bendixen & Hartley, 2003; Chen et al., 2006) it was assumed (Hypothesis 2) that learners with a more favorable pattern of learner characteristics (i.e., a higher level of prior knowledge, better self-regulatory skills, a preference for receiving large amounts of instruction, and more complex epistemological beliefs) would show more effective example utilization strategies (i.e., select modular examples more frequently, choose elaborated and incomplete examples only if necessary, and select examples to conduct helpful comparisons within and across problem categories);

also they would experience less cognitive load during learning (Hypothesis 3), and show better problem-solving performance (Hypothesis 4).

## 2. Method

### 2.1. Participants

Participants were 79 students (34 male, 45 female) of the University of Tuebingen, Germany, were paid to participate in the study (average age: 25.05 years,  $SD = 3.00$ ). Of them 22.8 percent were freshmen, 74.7 percent were sophomores, and 2.5 percent were senior students. The largest groups came from the Social Sciences (27.8%), Law and Business (24.1%), Teacher Education (22.8%), and the Natural Sciences (15.2%). The groups determined in the cluster analysis reported below (see Results) did not differ with regard to the distribution of any of these measures.

### 2.2. Materials – procedure

The hypermedia environment on probability theory consisted of a technical instruction, an introduction to the domain, an example-based learning phase, and a subsequent test phase. For the learning phase, learners were told that they had to acquire knowledge on four different problem categories, where each category was explained by two examples. To access an example, learners first had to select one of the problem statements from the left navigation bar (Fig. 2). For the problem statements two different types of cover stories were used: The urn examples always dealt with selecting marbles from an urn and thus had the same cover story across problem categories. The all-day examples were related to real-life situations and had varying cover stories across categories (see Appendix A for all-day examples).

Once a learner had selected one of the eight problem statements, it was displayed on the format-selection page together with eight hyperlinks that allowed retrieving different formats for the presentation of the solution procedure. These formats varied with regard to the *solution approach* (molar vs. modular examples), the *degree of elaboration* (highly-elaborated examples with detailed justifications for each solution step, medium-elaborated examples without further justifications, condensed examples with only mathematical expressions), and the *availability of self-explanation prompts*. Examples with self-explanation prompts were first presented in the medium-elaborated version. Learners were then prompted to type in the missing elaborations and to subsequently compare their elaborations to the highly-elaborated explanations that were presented to them. The latter explanations were then added to the examples' description. This cycle had to be repeated for each solution step and could not be terminated before the worked-out example was highly-elaborated.

The different degrees of elaboration and the self-explanation prompts were available for molar as well as for modular examples (see rows of Fig. 2). According to the provided

**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. Moreover, there are **incomplete examples**, where you will receive feedback for your completions. 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.

Fig. 2. Example-selection page (molar example formats were labeled 'formula-based approach' and modular example formats were labeled 'individual event probability approach' in the hypermedia environment).

options learners could choose among 64 formats of presentation (i.e., eight problem statements  $\times$  eight solution formats). The differences among these options were explained to learners on entering the learning phase. Moreover, a page with descriptions of the different formats was accessible via a hyperlink displayed on the format-selection page; however, this page was retrieved by only 11.4% of all learners. Students could start working on the test problems whenever they wanted by clicking a "Test"-button. Before solving the problems, learners had to give an estimate of their cognitive load and related variables.

## 2.3. Measures

### 2.3.1. Domain-specific prior knowledge

Eleven multiple-choice questions assessed students' domain-specific prior knowledge on important concepts in probability theory, whereby for each correct answer students were assigned one credit. A sample question was "What is meant by 'possible outcomes' in probability theory?" Cronbach's  $\alpha$  was .57 for this test.

All the other learner characteristics were assessed by translated and slightly modified versions of preexisting questionnaires. The responses to the questionnaires' items were based on five-point Likert-type response scales, whereby higher values indicated a stronger presence of the registered trait.

### 2.3.2. Use of cognitive and metacognitive strategies

The Domain-Specific Cognitive and Metacognitive Strategies questionnaire (Wolters, 2004) consisted of seven items to

estimate how inclined students are to apply cognitive strategies during studying mathematical contents (e.g., "I generate own examples that help to understand the main concepts in mathematics"; Cronbach's  $\alpha = .68$ ) and eight items to assess use of metacognitive strategies (e.g., "Before trying to solve a problem in mathematics, I think about the best way of approaching it"; Cronbach's  $\alpha = .69$ ).

### 2.3.3. Epistemological beliefs

Students' epistemological beliefs were registered with an instrument by Jacobson and Jehng (1999). Three scales assessed certainty of knowledge (nine items; e.g., "If scientists try hard enough, they can find an answer to almost every problem"; Cronbach's  $\alpha = .63$ ), knowledge acquisition as an orderly process (seven items; e.g., "If a problem has more than one solution, it is usually easy to find the best one"; Cronbach's  $\alpha = .18$ ), and quick learning (eight items; e.g., "I either understand a new topic on the first try or never"; Cronbach's  $\alpha = .58$ ).

### 2.3.4. Attitudes towards mathematics

Twenty items from the Attitudes towards Mathematics Inventory by Tapia and Marsh (2004) were used to assess students' self-confidence (5 items; e.g., "It makes me nervous to even think about having to do a mathematics problem"; Cronbach's  $\alpha = .94$ ), value (four items; e.g., "Mathematics is a very worthwhile and necessary topic"; Cronbach's  $\alpha = .73$ ), enjoyment (five items; e.g., "I have usually enjoyed studying mathematics in school"; Cronbach's  $\alpha = .83$ ), and motivation (six items; e.g., "The challenge of mathematics appeals to me"; Cronbach's  $\alpha = .84$ ).

### 2.3.5. Preferences for amount of instruction

Students' preferences for amount of instruction were assessed by a seven-item scale by Hannafin and Sullivan (1996). The questionnaire asked learners to indicate their agreement towards four domain-specific statements (e.g., "If I learn something new in mathematics, I want to review the content several times"). Moreover, students had to answer three domain-general questions (e.g., "If you learn something new, how much practice you want?"). The responses to the seven items were aggregated into a single score, where higher values indicated a stronger preference for receiving large amounts of instruction (Cronbach's  $\alpha = .72$ ).

### 2.3.6. Metacognitive activity

Contrary to the aforementioned measures, metacognitive activity was assessed after interacting with the hypermedia environment, as it was supposed to measure students' self-reported metacognitive behavior in the concrete situation. The Metacognitive Activity questionnaire (Schmidt & Ford, 2003) consisted of 15 statements, where learners had to indicate how often they showed metacognitive activities during learning (e.g., "During this training program, I tried to change the way I learned in order to fit the demands of the situation or topic"; Cronbach's  $\alpha = .83$ ).

### 2.3.7. Example utilization strategies

Students' example utilization strategies were assessed based on the frequency of retrieving urn or all-day example statements, of selecting either modular or molar examples, of retrieving highly-elaborated, medium-elaborated, or condensed examples, and of choosing examples with self-explanation prompts. As time data, we assessed the overall time spent on processing examples without self-explanation prompts. Moreover, we measured the time spent on the format-selection page as a potential indicator for metacognitive awareness.

### 2.3.8. Learning outcomes

Learning outcomes comprised self-reported cognitive load and problem-solving performance for the 11 test problems.

**2.3.8.1. Cognitive load.** Cognitive load was assessed by means of three items, which referred to (a) task demands (how much mental and physical activity was required to accomplish the learning task, e.g., thinking, deciding, calculating, remembering, looking, searching etc.), (b) effort (how hard the participant had to work to understand the contents of the learning environment), and (c) navigational demands (how much effort the participant had to invest to navigate the learning environment). The last item can be considered to assess extraneous load in hypermedia learning. The mapping of the first two items onto intrinsic and germane cognitive load is less evident, as learners usually cannot distinguish between demands inherent to the task (as suggested in the first item)

and demands caused by additional elaboration activities (as suggested in the second item) based on introspection.

Two additional items assessed feelings of success and experienced stress during learning.

All items had to be rated on a response scale from 0 (very low) to 10 (very high).

**2.3.8.2. Problem-Solving Performance test.** Performance was assessed for each of the 11 test problems, with one point assigned for each correct answer. The five isomorphic test problems differed from the instructional examples only with regard to their surface features. The six novel test problems were constructed in a way that two complex-event probabilities had to be considered, the outcomes of which had to be multiplied in order to calculate the required probability. A sample novel test problem was:

"At a soccer stadium, there are two dressing rooms for the two opposing teams. The 11 players from Oxford wear T-shirts with odd numbers from 1 to 21 and the 11 players from Manchester have even numbers from 2 to 22. Because the aisle from the dressing rooms is very narrow only one player at a time can enter the field. The players of the two teams leave their rooms alternately with a player from Oxford going first. What is the probability of the first five players entering the field having the numbers 5, 2, 13, 8, and 1 (i.e., the first has the number 5, the second has the number 2, and so on)?"

Cronbach's  $\alpha$  for the Problem-Solving Performance test was .79.

## 3. Results

### 3.1. Clusters of student characteristics

The  $z$ -standardized learner characteristics data were submitted to a cluster analysis using the common Ward algorithm based on the squared Euclidian distance as the recommended proximity measure. To determine the optimal number of clusters, the step within the agglomerative cluster analysis was identified, where a further merging of clusters would have yielded an unacceptable large increase in within-cluster variance (cf. stepsize criterion; Johnson, 1967). Thus, the clustering was terminated after five clusters had been formed (see Table 1). It was decided against stopping the clustering at an earlier point in the procedure, because this would have yielded rather small clusters.

To assess the quality of this solution, we first determined the homogeneity of each of the clusters with respect to the learner characteristics variables by calculating an  $F$ -score, where the within-cluster variance is divided by the overall variance for each variable. A good homogeneity is achieved if the within-group variance is less than the overall variance (i.e.,  $F < 1$ ). As can be seen in Table 2, this is the case for most of the comparisons made. Only students in Cluster 5 are rather heterogeneous with respect to all learner characteristics expect for their attitudes towards mathematics. In addition, the learner

Table 1  
Means (and standard deviations) of learner characteristics as a function of cluster.

Variables and ANOVA results	Cluster 1 ( <i>n</i> = 25)	Cluster 2 ( <i>n</i> = 14)	Cluster 3 ( <i>n</i> = 19)	Cluster 4 ( <i>n</i> = 9)	Cluster 5 ( <i>n</i> = 12)	Post-hoc Tukey tests
	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	<i>M</i> ( <i>SD</i> )	
<i>Prior knowledge</i>						
(% of correct answers) <i>F</i> (4, 74) = 4.95; <i>p</i> = .001, partial $\eta^2 = .21$	85.82 (9.85)	74.03 (21.65)	73.69 (16.01)	80.81 (16.67)	61.36 (20.56)	1 vs. 5**; 4 vs. 5 (*)
<i>Epistemological beliefs</i>						
Certainty of knowledge: <i>F</i> (4, 74) = 4.30; <i>p</i> = .003, partial $\eta^2 = .19$	3.37 (.63)	2.97 (.58)	3.73 (.47)	3.14 (.27)	3.23 (.63)	2 vs. 3**; 3 vs. 4 (*)
Orderly process: <i>F</i> (4, 74) = 4.09; <i>p</i> = .005, partial $\eta^2 = .18$	2.94 (.44)	3.43 (.41)	3.25 (.28)	3.22 (.33)	3.30 (.47)	1 vs. 2**; 1 vs. 3 (*) 1 vs. 5 (*)
Quick learning: <i>F</i> (4, 74) = 7.80; <i>p</i> < .001, partial $\eta^2 = .30$	4.15 (.30)	4.00 (.45)	4.11 (.41)	3.35 (.46)	3.92 (.39)	4 vs. all**
<i>Attitudes towards mathematics</i>						
Value: <i>F</i> (4, 74) = 27.08; <i>p</i> < .001, partial $\eta^2 = .59$	4.34 (.47)	3.57 (.65)	3.84 (.47)	3.50 (2.58)	2.58 (.47)	1,5 vs. all**
Motivation: <i>F</i> (4, 74) = 30.14; <i>p</i> < .001, partial $\eta^2 = .62$	3.71 (.57)	2.63 (.71)	2.25 (.44)	2.92 (.33)	1.87 (.62)	1 vs. all**; 5 vs. 1,2,4**; 3 vs. 4*
Enjoyment: <i>F</i> (4, 74) = 38.88; <i>p</i> < .001, partial $\eta^2 = .68$	4.13 (.59)	2.61 (.69)	2.34 (.54)	3.56 (.46)	1.78 (.83)	1,4 vs. all*; 2,3 vs. 5**
Confidence: <i>F</i> (4, 74) = 41.49; <i>p</i> < .001, partial $\eta^2 = .69$	4.15 (.48)	2.86 (.91)	1.88 (.60)	3.71 (.32)	1.87 (1.00)	1 vs. 2,3,5*; 4 vs. 2,3,5*; 3 vs. 5**
<i>Cognitive strategies</i>						
<i>F</i> (4, 74) = 8.74; <i>p</i> < .001, partial $\eta^2 = .32$	3.38 (.61)	3.41 (.44)	2.76 (.35)	3.00 (.57)	2.45 (.71)	3 vs. 1,2**; 5 vs. 1,2**
<i>Metacognitive strategies</i>						
<i>F</i> (4, 74) = 9.19; <i>p</i> < .001, partial $\eta^2 = .33$	3.49 (.57)	3.48 (.31)	3.07 (.40)	3.03 (.41)	2.56 (.62)	5 vs. 1,2,3*; 1 vs. 3*
<i>Preference for amount of instruction</i>						
<i>F</i> (4, 74) = 7.25; <i>p</i> < .001, partial $\eta^2 = .28$	4.07 (.44)	4.67 (.23)	4.17 (.54)	3.75 (.61)	3.83 (.54)	2 vs. all*
<i>Metacognitive activity</i>						
<i>F</i> (4, 74) = 2.71; <i>p</i> = .04, partial $\eta^2 = .13$	3.31 (.69)	3.47 (.46)	3.05 (.64)	2.94 (.43)	2.80 (.66)	2 vs. 5 (*)

\*\**p* ≤ .01; \**p* ≤ .05; (\*)*p* ≤ .10.

1, 2, 3, 4, 5 = Cluster 1, 2, 3, 4, 5, respectively.

characteristics data were submitted to a discriminant analysis as suggested by Backhaus, Erichson, Plinke, and Weiber (1993). Despite the fact that cluster analysis and discriminant analysis use the data in different ways, the fit between the two methods was almost perfect. That is, in 77 out of 79 cases (97.5%) the discriminant analysis assigned students to the clusters that had been previously determined with the cluster analysis. This high fit also indicates that one of the major problems associated with hierarchical cluster algorithms, namely, that they may result in early undesirable ties that persist throughout the further procedure, could be avoided.

The average discriminant coefficients emerging from this analysis were used to determine the contribution of each learner variable within the context of the other variables for deciding about each individual's cluster (see last column of Table 2). The larger these coefficients are, the more the variable contributes to the separation of clusters. Because this

method determines the relative strength of contribution of each variable, it also allows detecting redundancies among variables. Thus, a variable will have a weak discriminating function, if the same separation can be achieved by another variable already. The discriminant analysis revealed that students' prior knowledge as well as the way they valued mathematics contributed most strongly to the separation of clusters. Moreover, none of the variables was irrelevant to the definition of clusters. On the contrary, there were quite a few variables that had a strong predictive value for cluster separation, showing the variables' contribution beyond prior knowledge.

To analyze the different cluster profiles, the five clusters were compared by means of multiple one-factor ANOVAs followed by post-hoc Tukey tests according to the different learner characteristics (see Table 1). The overall differences across the five clusters were all highly significant.



Table 2  
Homogeneity indices and average discriminant coefficients for the learner characteristics variables as a function of cluster.

Variables	Cluster 1 (n = 25)	Cluster 2 (n = 14)	Cluster 3 (n = 19)	Cluster 4 (n = 9)	Cluster 5 (n = 12)	Discriminant coefficient
<i>Prior knowledge (% correct answers)</i>	.30	1.45	.79	.86	1.31	3.06
<i>Epistemological beliefs</i>						
Certainty of knowledge	1.11	.94	.61	.19	1.08	1.30
Orderly process	1.06	.94	.44	.61	1.22	.93
Quick learning	1.45	1.00	.85	1.05	.75	.98
<i>Attitudes towards mathematics</i>						
Value	.39	.75	.39	.16	.39	3.35
Motivation	.42	.66	.25	.13	.49	1.89
Enjoyment	1.30	.41	.25	.18	.59	1.56
Confidence	1.16	.57	.25	.07	.70	2.91
<i>Cognitive strategies</i>	.93	.46	.29	.78	1.24	.76
<i>Metacognitive strategies</i>	1.00	.30	.48	.52	1.15	1.46
<i>Preference for amount of instruction</i>	.30	.17	.97	1.23	1.00	1.40
<i>Metacognitive activity</i>	.67	.51	.98	.46	1.07	.75

The homogeneity is the ratio of within-cluster variance relative to the overall variance.

Moreover, the difference between the cluster mean and the overall mean was calculated for each learner characteristic and divided by the overall standard deviation as a measure of effect size that provides information on whether the cluster profile is sufficiently distinct from the sample as a whole (Table 3). Based on the results of the two analyses, predictions were made for each of the five clusters concerning the suitability of the learner characteristic profiles for achieving positive learning outcomes.

Students in *Cluster 1* had a high level of prior knowledge, tended to believe in learning as a slow process, valued and enjoyed mathematics, were motivated and confident when dealing with mathematical problems, deployed cognitive as well as metacognitive strategies frequently, preferred rather large amounts of instruction, and reported having been metacognitively active during learning. Only their conviction that learning is a rather orderly process indicated simplistic epistemological beliefs. Learners in Cluster 1 form one end of a continuum reaching from favorable to unfavorable prerequisites for successful learning and are thus expected to show adaptive strategies of using information, to experience low levels of cognitive load, and demonstrate a good problem-solving performance.

Learners in *Cluster 5* build the opposite end of this continuum. Specifically, they had a low level of prior knowledge, disvalued and disliked mathematics, did not enjoy or feel confidence in dealing with mathematical challenges, reported a sparse use of cognitive and metacognitive strategies in general and during the interaction with the environment, and did not show a clear preference for receiving lots of instructional materials. Their epistemological beliefs were at an intermediate level of complexity. Taken together, the profile

of Cluster-5 students suggests that they would show an inadequate utilization of information, a high level of cognitive load, and low problem-solving performance.

The three remaining clusters of learners fall in between these extreme positions, but for different reasons. Students in *Cluster 4* had a rather high level of prior knowledge, had simpler epistemological beliefs in terms of the certainty of knowledge and the speed by which it is acquired, valued and were motivated towards mathematics at an intermediate level, but enjoyed it and were highly confident in dealing with the domain. Their cognitive and metacognitive strategy use, preferences for amount of instruction, and self-reported metacognitive activity were not distinct from others. Learners in Cluster 4 are expected to perform better than students in Cluster 5, although probably less good than students in Cluster 1 in terms of their information utilization strategies, cognitive load, and problem-solving performance.

Students in Clusters 2 and 3 were alike with respect to their intermediate level of prior knowledge, rather complex epistemological beliefs in terms of the orderliness and speed of knowledge acquisition, and their intermediate value as well as low motivation and enjoyment assigned to mathematics. However, some differences in the two profiles suggested that Cluster 2 would perform better than Cluster 3. *Cluster 2* resembled Cluster 1 in that both clusters frequently deployed cognitive and metacognitive strategies and reported being metacognitively active. Moreover, Cluster 2 had the strongest preference for large amounts of instruction of all clusters. It might thus well be that these students, despite a lack of positive attitudes towards mathematics, were willing to invest time and effort into cognitive and metacognitive activities during learning. Students in *Cluster 3*, on the other hand, had

Table 3  
Standardized differences between cluster means and overall mean for the learner characteristics variables as a function of cluster.

Variables	Cluster 1 (n = 25)	Cluster 2 (n = 14)	Cluster 3 (n = 19)	Cluster 4 (n = 9)	Cluster 5 (n = 12)
<i>Prior knowledge (% correct answers)</i>	.52	-.14	-.16	.24	-.84
<i>Epistemological beliefs</i>					
Certainty of knowledge	.05	-.62	.65	-.33	-.18
Orderly process	-.60	.57	.14	-.07	.26
Quick learning	.35	.02	.27	-1.42	-.16
<i>Attitudes towards mathematics</i>					
Value	.83	-.20	.16	.29	-1.52
Motivation	1.03	-.19	-.63	.15	-1.05
Enjoyment	1.06	-.34	-.59	.35	-1.11
Confidence	.98	-.10	-.92	.61	-.93
<i>Cognitive strategies</i>	.52	.56	-.45	-.08	-.94
<i>Metacognitive strategies</i>	.52	.50	-.21	-.28	-1.09
<i>Preference for amount of instruction</i>	-.11	.98	.07	-.69	-.55
<i>Metacognitive activity</i>	.23	.48	-.17	-.33	-.55

negative attitudes towards mathematics that resembled those of Cluster 5. Although they valued mathematics, they were not motivated towards it, did not enjoy dealing with mathematics or feel any confidence in it. Moreover, their self-reported frequency of using cognitive and metacognitive strategies was almost as low as that of learners in Cluster 5. For these reasons, it is expected that the students in Cluster 3 will be similar to those of Cluster 5 and thus perform less well than students in Clusters 1, 2, and 4. For the latter three clusters, the best performance is expected for students in Cluster 1, whereby no prediction can be made for distinguishing students in Clusters 2 and 4.

### 3.2. Example utilization strategies as a function of cluster

For the comparison of example utilization strategies (Table 4), we conducted three MANOVAs to account for the

types of decisions a learner had to make with respect (a) to the type of cover story for the problem statements (urn vs. all-day), (b) the solution approach (molar vs. modular), and (c) the degree of elaboration (high vs. medium vs. condensed). For the time data and the frequency of retrieving examples with self-explanation prompts separate ANOVAs were computed. The between-subjects factor in the (M)ANOVAs was Cluster.

The clusters tended to differ in the time spent on the format-selection page,  $F(4, 74) = 2.39$ ,  $p = .06$ , partial  $\eta^2 = .11$ . In particular, students in Cluster 2 spent longer times on this page than students in Cluster 3 ( $p = .06$ ). There were no differences for the overall time spent on worked examples,  $F < 1$ .

#### 3.2.1. Type of cover story

With respect to the frequency of retrieving urn and all-day examples, the  $5(\text{cluster}) \times 2(\text{type of cover story})$  MANOVA

Table 4  
Means (and standard deviations) of example utilization strategies as a function of cluster.

Strategies	Cluster 1 (n = 25)	Cluster 2 (n = 14)	Cluster 3 (n = 19)	Cluster 4 (n = 9)	Cluster 5 (n = 12)
<i>Time (s)</i>					
Format-selection page	281.20 (192.75)	440.07 (252.38)	216.37 (238.49)	404.00 (342.05)	270.83 (180.88)
Worked examples	459.76 (348.68)	498.64 (203.51)	564.84 (475.05)	382.22 (277.96)	471.50 (233.68)
<i>Frequency</i>					
Urn examples	9.08 (5.20)	10.79 (6.49)	8.16 (6.19)	10.56 (4.53)	6.83 (2.59)
All-day examples	7.48 (3.85)	7.79 (4.77)	4.42 (2.80)	7.44 (3.71)	5.33 (3.65)
Molar examples	8.96 (6.50)	11.79 (5.31)	6.58 (6.74)	5.00 (5.38)	7.00 (6.22)
Modular examples	7.60 (6.61)	6.79 (7.36)	6.00 (4.75)	13.00 (6.25)	5.17 (5.08)
Highly-elaborated examples	5.76 (4.92)	9.86 (9.04)	7.58 (6.21)	6.00 (6.52)	6.58 (4.29)
Medium-elaborated examples	3.44 (6.04)	4.21 (5.08)	2.95 (3.91)	7.22 (6.82)	2.42 (2.30)
Condensed examples	7.36 (7.20)	4.50 (4.99)	2.05 (4.67)	4.78 (3.73)	3.17 (4.28)
Examples with self-explanation prompts	4.68 (11.95)	3.71 (7.04)	1.47 (1.50)	2.89 (2.47)	3.83 (7.17)

Table 5  
Means (and standard deviations) of learning outcomes as a function of cluster.

Learning outcomes	Cluster 1 ( $n = 25$ )	Cluster 2 ( $n = 14$ )	Cluster 3 ( $n = 19$ )	Cluster 4 ( $n = 9$ )	Cluster 5 ( $n = 12$ )
<i>Cognitive load (0–10)</i>					
Task demands	4.28 (2.06)	5.50 (2.35)	6.00 (2.60)	4.67 (2.17)	7.00 (1.90)
Effort	2.52 (1.62)	4.04 (1.91)	4.63 (2.59)	2.72 (1.73)	6.08 (2.37)
Navigational demands	1.14 (1.45)	1.46 (1.70)	3.08 (2.33)	.61 (0.49)	2.33 (2.26)
Feelings of success	7.28 (1.61)	7.68 (1.07)	6.42 (1.48)	6.06 (2.59)	4.83 (2.07)
Stress	1.76 (1.82)	3.57 (2.45)	4.76 (2.64)	2.44 (2.57)	5.46 (2.71)
<i>Performance</i> (% correct answers)					
Isomorphic problems	61.60 (27.03)	60.00 (28.28)	29.47 (30.09)	75.56 (16.67)	38.33 (34.60)
Transfer problems	42.67 (32.66)	21.43 (28.06)	10.53 (19.41)	44.44 (40.82)	13.89 (30.01)

revealed a main effect of cover story, Pillai's trace = .18,  $F(1, 74) = 16.11$ ,  $p < .001$ , partial  $\eta^2 = .18$ . Students preferred studying urn examples ( $M = 8.99$ ,  $SD = 5.38$ ) to all-day examples ( $M = 6.49$ ,  $SD = 3.93$ ). There was no interaction of cluster with cover story,  $F < 1$ . In the univariate analyses the five clusters did not differ in the frequency of using urn examples,  $F(4, 74) = 1.19$ ,  $p > .30$ , partial  $\eta^2 = .06$ , but in the frequency of using all-day examples,  $F(4, 74) = 2.71$ ,  $p = .04$ , partial  $\eta^2 = .13$ .

### 3.2.2. Solution approach

The 5(cluster)  $\times$  2(solution approach) MANOVA showed that there was no overall preference for selecting either molar or modular examples, Pillai's trace  $< .01$ ,  $F < 1$ . However, there was an interaction between the solution approach and cluster, Pillai's trace = .12,  $F(4, 74) = 2.54$ ,  $p = .047$ , partial  $\eta^2 = .12$ , demonstrating that molar examples tended to be chosen more often than modular examples by students in Cluster 2 ( $p = .06$ ), whereas learners in Cluster 4 had a clear preference for modular examples ( $p = .02$ ). The other clusters showed a balanced retrieval of both example formats. The univariate analyses revealed no differences across the five clusters for the molar approach,  $F(4, 74) = 2.29$ ,  $p = .07$ , but there was a significant effect of cluster in the modular approach,  $F(4, 74) = 2.59$ ,  $p = .04$ , partial  $\eta^2 = .12$ . The post-hoc comparisons, however, showed only that students in Cluster 4 tended to retrieve modular examples more frequently than those in Cluster 3 ( $p = .06$ ) and Cluster 5 ( $p = .05$ ).

### 3.2.3. Degree of elaboration

The 5(cluster)  $\times$  3(degrees of elaboration) MANOVA showed that there was a significant effect of the degree of elaboration, Pillai's trace = .11,  $F(2, 73) = 4.51$ ,  $p = .02$ , partial  $\eta^2 = .11$ . There were overall differences in the frequency of retrieving highly-elaborated, medium-elaborated, and condensed examples, which were caused by the fact that the students preferred highly-elaborated ( $M = 7.08$ ,  $SD = 6.25$ ) to medium-elaborated examples ( $M = 3.73$ ,  $SD = 5.27$ ,  $p = .005$ ), and to condensed examples ( $M = 4.65$ ,  $SD = 5.79$ ,  $p = .02$ ). There was no interaction between the degree of elaboration and clusters,  $F(8, 148) = 1.48$ ,  $p > .10$ . The univariate analyses showed no differences between clusters for retrieving either highly-elaborated examples,

$F(4, 74) = 1.09$ ,  $p > .30$ , or medium-elaborated examples,  $F(4, 74) = 1.35$ ,  $p > .20$ . However, cluster differences were found for the frequency of using condensed examples,  $F(4, 74) = 2.75$ ,  $p = .03$ , partial  $\eta^2 = .13$ , which were retrieved more often by students in Cluster 1 than in Cluster 3 ( $p = .02$ ).

An ANOVA with cluster as independent variable and retrieving examples with self-explanation prompts as dependent variable revealed no main effect of cluster,  $F < 1$ .

### 3.3. Learning outcomes

The final analyses assessed whether the differences in clusters would affect learning outcomes during learning (see Table 5).

#### 3.3.1. Cognitive load

The ANOVAs with cluster as independent variable and each of the measures of cognitive load, that is, task demands, effort, navigational demands, feelings of success, and stress experienced during learning showed the following: for task demands,  $F(4, 74) = 3.67$ ,  $p = .009$ , partial  $\eta^2 = .17$ ; for effort,  $F(4, 74) = 7.44$ ,  $p < .001$ , partial  $\eta^2 = .29$ ; for navigational demands,  $F(4, 74) = 4.53$ ,  $p = .003$ , partial  $\eta^2 = .20$ ; for feelings of success,  $F(4, 74) = 5.82$ ,  $p < .001$ , partial  $\eta^2 = .24$ ; for stress experienced during learning,  $F(4, 74) = 7.20$ ,  $p < .001$ , partial  $\eta^2 = .28$ . The lowest task demands were reported by students in Cluster 1, which was less than that of students in Cluster 5 ( $p = .008$ ). The effort ratings were the highest in Cluster 5, which was the low prior knowledge cluster, compared to Cluster 1 ( $p < .001$ ), and Cluster 4 ( $p = .004$ ). Moreover, students in Cluster 3 reported higher effort investments than those in Cluster 1 ( $p = .01$ ). Similarly, students in Cluster 3 rated the navigational demands higher than their counterparts in Cluster 1 ( $p = .007$ ), and Cluster 4 ( $p = .01$ ). Feelings of success were lowest for students in Cluster 5, which differed significantly from Cluster 1 ( $p = .001$ ) and Cluster 2 ( $p = .002$ ). Finally, students in Cluster 5 experienced a higher level of stress compared to those of Cluster 1 ( $p < .001$ ) and Cluster 4 ( $p < .05$ ), respectively. Similarly, students in Cluster 3 felt more stressed during learning than those in Cluster 1 ( $p = .001$ ).

### 3.3.2. Performance

The ANOVAs regarding the effects of clusters on performance showed that the five clusters differed significantly in their performance on isomorphic problems,  $F(4, 74) = 6.23$ ,  $p < .001$ , partial  $\eta^2 = .25$ , and on transfer problems,  $F(4, 74) = 3.52$ ,  $p = .01$ , partial  $\eta^2 = .16$ . Both differences correspond to large effect sizes. Post-hoc comparisons revealed that the performance differences were in line with differences in self-reported cognitive load and related variables as students with lower levels of cognitive load, stronger feelings of success, and less stress also showed better performance.

When solving isomorphic problems, students in Cluster 3 achieved the lowest performance, which differed significantly from performance of students in Cluster 1 ( $p = .003$ ), Cluster 2 ( $p = .03$ ), and Cluster 4 ( $p = .001$ ), but not of students in Cluster 5 ( $p > .90$ ). Moreover, participants in Cluster 5 solved fewer problems correctly than those in Cluster 4 ( $p = .03$ ). None of the other differences were significant. According to these results, the five clusters can be classified as either being successful problem solvers (Clusters 1, 2, and 4) or unsuccessful problem solvers (Clusters 3 and 5). With regard to transfer performance, the lowest performance was again achieved by Cluster 3, which was significantly less than that of Cluster 1 ( $p = .01$ ), but failed to differ significantly from Cluster 4 ( $p = .12$ ). None of the other differences were significant, which was mainly caused by the large within-group variances. On a descriptive level, students in Clusters 1 and 4 achieved the same high transfer performance, whereas those in Clusters 3 and 5 both scored low. For transfer performance, students in Cluster 2 did not keep up with the performance level of Clusters 1 and 4, although the differences between the first and the latter two clusters were not significant.

## 4. Discussion

The present study investigated the impact of profiles of learner characteristics on information utilization strategies, cognitive load during learning, and problem-solving performance in an example-based hypermedia environment. In line with Hypothesis 1 we were able to identify distinct clusters of learners, who differed according to their learner characteristics. In Hypothesis 2, it had been assumed that learners with a more favorable pattern of learner characteristics would show more effective example utilization strategies. Differences among the clusters were found in line with this assumption, although the effects of learner characteristics on example utilization strategies were weaker than had been initially expected. Finally, learners with more favorable characteristics experienced less cognitive load (Hypothesis 3) and showed better problem-solving performance (Hypothesis 4). The findings with regard to these hypotheses will be discussed in more detail in the following.

Students in Cluster 1 were more than a quarter of learners, possessed very promising learner characteristics in terms of their prior knowledge, epistemological beliefs, self-regulation

abilities, and preferences for amount of instruction. They showed a balanced processing of the different example formats except for their preference of condensed examples to highly-elaborated examples. This is adaptive, as they possess the prior knowledge necessary to generate explanations for the solution procedures of the example problems themselves. Their behavior thus corresponds to the suggestion by Renkl (2002) to provide instructional explanations only if learners are not able to generate self-explanations. As expected, these students experienced only moderate levels of cognitive load and stress, reported strong feelings of success, and scored high in terms of problem-solving performance.

Students in Cluster 4 comprised a rather small cluster very similar to the students in Cluster 1 in terms of their high level of prior knowledge and confidence when dealing with mathematics. However, their other attitudes towards mathematics were less positive. Nevertheless, these students were still able to regulate their learning behavior in adaptive ways. Most importantly, they were the only cluster to clearly prefer modular examples. This adaptive information selection together with favorable learner characteristics paid off as observable in the students' cognitive load pattern and problem-solving performance.

Students in Cluster 2, which were almost as successful as students in Clusters 1 and 4, resembled the very unsuccessful students in Cluster 3 in terms of prior knowledge, epistemological beliefs, and a relatively negative attitude towards mathematics. However, students in Cluster 2 were able to counteract their dislike of mathematics by a frequent use of cognitive and metacognitive self-regulation strategies. Their high level of metacognitive activity during learning was also reflected in the very long times they spent on selecting an example format, which may indicate intensive reflections concerning the usefulness of the different presentation formats made available through this page. Thus, their data show how the presence of some positive learner characteristics may compensate for a lack of others. Moreover, students in Cluster 2 showed the strongest preference compared to students in all other clusters for receiving large amounts of instruction, which on a behavioral level was in accordance with their frequent retrieval of highly-elaborated examples. However, in contrast to their performance for isomorphic problems, their performance deteriorated for transfer problems. This dissociation may provide first evidence for the relative impact of different learner characteristics: Motivation and a high level of prior knowledge might be necessary prerequisites for achieving the deeper understanding needed for accomplishing transfer tasks, whereas their lack can be compensated for working on simpler tasks.

Students in Clusters 3 and 5 resembled each other in qualitative ways, though quantitatively, Cluster 5 had the least favorable learner characteristics. Students in both Clusters 3 and 5 reported a higher occurrence of navigational problems, which might hinder learning as they imposed extraneous load onto learners (Dias, Gomes, & Correia, 1999). These findings replicate prior hypermedia research indicating that students with less favorable learning prerequisites are most prone to

navigational problems (Lawless & Kulikowich, 1996; McDonald & Stevenson, 1998). One thing that is important though is that students in Cluster 5 had a rather realistic estimate of their learning progress as reflected in their reduced feelings of success. Students in Cluster 3, on the other hand, overestimated their progress and, therefore, seemed to suffer from illusions of understanding (Renkl, 2002). The latter students might thus be particularly endangered in learner-controlled settings, as they might not feel the necessity to adapt their learning behavior to their knowledge gaps.

It is important to note that while prior knowledge proved to be important for defining the learner clusters, the other learner characteristics considered in this study evidently had their own distinct contribution to the findings. In particular, students' attitudes towards mathematics were very important for defining clusters. Moreover, it was only Clusters 1 and 5 that differed significantly in their prior knowledge. Despite the similarities among Clusters 2, 3, and 4 concerning prior knowledge, students in Clusters 2 and 4 showed a much better problem-solving performance than students in Cluster 3, which might be explained by their differences in terms of either better meta-cognitive skills of Cluster 2 or more complex epistemological beliefs and more positive attitudes of Cluster 4. Thus, these findings provide some support for the notion expressed in the augmented CLT model by Gerjets and Hesse (2004) that beyond prior knowledge other learner characteristics need to be taken into account in learner-controlled instruction. Moreover, epistemological beliefs and (meta-)cognitive strategy availability proved to be non-redundant. This contradicts findings by Bråten and Strømsø (2005), who suggested that – depending on academic context – epistemological beliefs predict self-regulation strategies due to the strong interdependency of the two constructs.

Despite these promising results regarding the impact of learner characteristics on interactive knowledge construction, at least two limitations need to be considered: First, the data for the epistemological beliefs questionnaire appeared to be inconsistent in some ways. That is, the unsuccessful students in Cluster 5 were characterized by rather complex epistemological beliefs, whereas successful students in Cluster 1 naïvely believed in learning as an orderly process. It appears that orderliness for the latter students might rather be an indication of the confidence they have in their knowledge than of their beliefs concerning learning and knowledge in general. Analogously, Bendixen and Hartley (2003) found that the naïve belief that learning occurs quickly was related to better learning outcomes in their hypermedia environment. Beyond this lack in validity, the orderly-process scale did not prove to be a reliable measure (Cronbach's  $\alpha = .18$ ); all other questionnaires had at least satisfactory reliabilities. Finally, for future studies it might be advised to use both, domain-general and domain-specific measures of epistemological beliefs to assess their relative contribution to interactive knowledge acquisition (cf. Schommer-Aikins et al., 2005; Strømsø, Bråten, & Samuelstuen, 2008).

Second, the relationship between learner characteristics as measured by paper-pencil questionnaires and information

utilization strategies assessed through logfiles was rather weak. Two reasons may be responsible for this finding: (a) self-reports on personal characteristics may not be a good predictor for observable learning behavior. Accordingly, Winne, Jamieson-Noel, 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 metacognitive abilities. However, then logfile data can no longer be used as an indicator of information utilization strategies irrespective of a learner's specific characteristics. (b) The information utilization strategies assessed were defined at a very coarse level. In particular, they did not provide information on how students cognitively processed the selected examples. Therefore, in future studies logfile analyses should be supplemented by more fine-grained measures that can be obtained through think-aloud techniques, eyetracking, or a combination of both (cf. Van Gog, Paas, & van Merriënboer, 2005). Multi-method approaches can be successful in further analyzing the high variability within clusters of learners (cf. Davidson-Shivers, Rasmussen, & Bratton-Jeffery, 1997 for a combination of video recordings, think-aloud protocols, and structured interviews).

Despite these weak relations between learner characteristics and information utilization strategies, there are two more interesting findings obtained from this data. First, students irrespective of their learner characteristics profile preferred urn examples to all-day examples, although one might have assumed that the latter would appear more appealing to them. Moreover, combining urn and all-day examples would have allowed making effective within-category comparisons of examples with varying surface features (Cummins, 1992; Quilici & Mayer, 1996). On the other hand, focusing on urn examples may have its benefits, because less irrelevant information related to an example's cover story needs to be processed and students can rely on the examples' repetitive structure. Thereby, selecting urn examples facilitates the comparison of examples across categories, because only the structural features vary across these examples. Across-category comparisons have been shown to be less cognitively demanding for students, require less time or instructional support, and frequently lead to better problem-solving performance than comparing multiple examples within problem categories (Scheiter & Gerjets, 2005). Based on the present data, however, it is unclear whether students preferred urn examples for these reasons.

The second interesting finding concerning students' information utilization strategies is that only students in Cluster 4 preferred modular to molar examples despite the lower efficiency for learning of the latter. There are at least two possible explanations for this finding: (a) students in Germany are more familiar with molar examples, that is, 'recipe-like' examples based on formulas, because these are heavily used in mathematics textbooks; (b) the major advantage of molar examples is that they are computationally-friendly, as multiple solution steps are collapsed into a single formula that represents the solution procedure (Atkinson et al., 2003). However, understanding the rationale of problems in probability theory can be

much better conveyed by means of modular examples, where a single structural feature is directly transferred into one part of the solution procedure. This may also explain why students in Cluster 4 had such a good problem-solving performance, particularly with regard to transfer performance. With respect to learner-controlled instruction, this sheds some doubt on whether one should allow students to select among different representational formats. If students are mainly oriented towards avoiding obvious mental effort and reject formats that appear too demanding to them, then these formats should not be included in hypermedia environments, even if more advanced learners (who have already understood the underlying principles) might derive some benefit from them.

To conclude, the study contributes to the position that the same hypermedia features that may be potentially effective for learning can be detrimental at the same time. This trade-off may be different depending on which characteristics a learner possesses. It provides further support for the augmentation of CLT (Gerjets & Hesse, 2004; Gerjets & Scheiter, 2003) for learner-controlled settings as it demonstrates that there are other variables beyond prior knowledge and instructional-design features, which may affect the emerging pattern of cognitive load and learning outcomes. These variables may thereby weaken the direct relationship between design aspects and cognitive load traditionally assumed in CLT.

## Appendix A. All-day examples

1. At the Olympics 7 sprinters participate in the 100 m-sprint. What is the probability of correctly guessing the winner of the gold, the silver, and the bronze medals?
2. A bank distributes a random four-digit secret code as a personal identification number (PIN) for its credit cards. Suppose one credit card has been lost. What is the probability that anybody finding the card and trying to get money with it will guess the correct secret code on the first try?
3. You are playing cards with your friends. The card game contains 52 cards and each person gets 4 cards. First, you receive all your cards and then your friends receive their cards. What is the probability that you get all four aces?
4. A car rental service owns 10 cars, each of which has a unique color. Within 14 days a person rents a car twice and chooses the car randomly. What is the probability of getting a red car one of the times and a blue one the other time?

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