Instructional Aids to Support a Conceptual Understanding of Multiple Representations

Kirsten Berthold and Alexander Renkl
University of Freiburg

The main goals of this study were to test whether multiple representations, such as diagrams and equations, per se help to acquire conceptual understanding in probability, and to investigate whether learners need instructional support to utilize the potentials of multiple representations. The authors conducted an experimental study with 8 conditions in which high school students (N = 170) studied worked examples from probability. The authors varied the type and number of representations and the availability of 2 support procedures: (a) a relating aid that used color codes and flashing to help learners see which elements in different representations corresponded to each other on a surface level and (b) self-explanations prompts to ensure that learners integrate corresponding parts in different representations on a structural level. The authors found that multiple representations per se did not foster conceptual understanding; however, both support procedures enhanced it. Yet, the self-explanation prompts did not only foster conceptual understanding by eliciting elaborations directed to domains principles but also incorrect elaborations that hindered the acquisition of procedural knowledge. Hence, self-explanation prompts are an instructional support procedure that can have conflicting effects on learning outcomes.

Keywords: multiple representations, integration, self-explanations, learning mathematics

During recent years, the substantial increase of multimedia learning environments has raised the question of whether combinations of representations such as diagrams, equations, tables, text, and graphs are actually helpful. Do such multiple external representations (MERs) inherently help to acquire conceptual understanding? Do learners need instructional aids in order to process and integrate the information provided by different representations? These are important questions both for research as well as for instructional designers and school teachers, to gain knowledge of how to exploit the potentials of multimedia learning environments.

Learning With Multiple Representations

Several theories emphasize the importance of MERs. For example, Mayer (2005a) described a theory of multimedia learning, which states that learners acquire more knowledge when they receive MERs in the form of text and pictures (multimedia principle). Also, proponents of cognitive constructivism emphasize the benefits of using MERs of concepts and information (Spiro, Feltovich, Jacobson, & Coulson, 1995).

Ainsworth (2006) emphasized in her theoretical account of learning from MERs that learners have to integrate information from MERs to construct conceptual understanding (constructing function; Ainsworth, 2006; see also Roy & Chi, 2005; Sternberg & Frensch, 1993). Thus, integration is considered the key mechanism in utilizing the potential of MERs when the major goal of instruction is conceptual understanding. By integration, the learners actively construct a conceptual knowledge representation that relates and integrates different kinds of information from diverse codalities (i.e., different representational systems; e.g., an arithmetical representation and a pictorial representation; see Weidenmann, 1997) into a coherent structure (Schnitz & Bannert, 2003). This process usually includes abstraction (see Ainsworth, 2006), for example, abstracting from the surface feature of multirepresentational solutions (e.g., specific objects and numbers) to the underlying structure in terms of a conceptual integration (Renkl, 2005). An example of relating surface features of a multirepresentational solution to each other is if a learner maps the multiplication sign of the arithmetical equation in Figure 1 on the ramifications of the tree diagram. However, it is important for such abstraction processes to go beyond simply relating corresponding elements in different representations (see Ainsworth, 2006), which do not involve a transformation of knowledge. Thus, with respect to the
multirepresentational solution in Figure 1, the learners have to structurally integrate the multiplication sign of the arithmetical equation and the ramifications of the pictorial tree diagram to understand the underlying structure, that is, that the multiplication sign stands for the inclusion of all possible combinations represented by the 20 branches in the pictorial tree diagram. Accordingly, Seufert and Brünken (2004) proposed that learners can only gain conceptual understanding when they engage in integrating the corresponding elements and structures of the MERs on a structural level in order to build up a more abstract and coherent knowledge structure. However, empirical research has shown that the expected effects of MERs often do not occur (e.g., Chandler & Sweller 1992; de Jong et al., 1998; van Someren, Reimann, Boshuizen, & de Jong, 1998). Especially the integration of MERs is highly demanding for learners, as several studies have shown (e.g., Anzai, 1991; Moreno & Durán, 2004; Moreno & Mayer, 1999; Schoenfeld, Smith, & Arcavi, 1993; for an overview see Seufert, 2003). For example, Ainsworth, Bibby, and Wood (2002) compared children learning how to estimate either with mathematical representations, pictorial representations, or a mixture of both. The single representations were used successfully and both fostered learning. However, the mixture of both had negative effects. In addition, a measure of representational coordination did not improve over time. Thus, it was possible to isolate the problem as resulting from relating representations. This suggests that learners are overwhelmed with the demand to integrate MERs (see also Ainsworth, 2006). When confronted with MERs, learners fail to link different representations or do not try at all and concentrate merely on one type of representation (Ainsworth, Bibby, & Wood, 1998). Similarly, guiding learners to integrate MERs has been found to be far from trivial (de Jong et al., 1998).

Taken together, the frequently found lack of effects of MERs can be ascribed to suboptimal integration processes. If learners fail to integrate MERs, the construction of conceptual understanding cannot be accomplished (see constructing function; Ainsworth, 2006). It is important to note that integrating MERs can heavily demand cognitive resources (Seufert & Brünken, 2006). First, the learners have to relate corresponding parts of the MERs with each other. This type of relating can be accomplished on a surface level and does not necessarily mean that the learners consider structural aspects (see Seufert & Brünken, 2004). Secondly, the learners have to integrate the corresponding aspects on a structural level in order to gain conceptual understanding. Against this background, it appears to be important to instructionally guide the learners in a twofold way: (a) a relating aid can help the learners to identify corresponding parts in different representations and (b) prompts can direct the learners’ attention to the structural level that ab-

5. Example Task: Mountainbike III

You and your friend take part in a two-day mountain bike course. Each day of the course the instructor brings along 5 helmets, each one of a different colour (orange, silver, brown, red, and green). The helmets are handed out randomly and given back to the instructor at the end of the day.

What is the probability that you and your friend get the red and the green helmet on the first day of the course (it does not matter who gets which colour)?

\[
\text{acceptable outcomes} \quad \frac{2}{5} \quad \text{me} \quad \frac{1}{4} \quad \text{friend} = \frac{2}{20}
\]

\[\text{The probability is} \quad \frac{2}{20}.\]

Figure 1. Screenshot of the learning environment of condition “pictorial and arithmetical solutions/relating aid/scaffolding self-explanation prompts.” o = orange; s = silver; b = brown; r = red; g = green.
stracks from the specifics of a given problem and its multirepresentational solution.

**Supporting Integration on a Surface Level by Relating Aids**

Instructional aid procedures for relating MERs that rely on surface features such as color code (i.e., assigning the same color to corresponding elements), shape, or arrows (e.g., Seufert & Brünken, 2006) were in particular investigated within research on cognitive load theory (e.g., Paas, Renkl, & Sweller, 2003; Sweller, 2005; Sweller, van Merriënboer, & Paas, 1998). This theory is concerned with the design of instructional materials that prevents unnecessary load on learners’ working memory capacities in order to help them efficiently use their limited cognitive processing capacity for learning processes (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). According to Paas and van Merriënboer (1994), cognitive load can be defined as a multidimensional construct representing the load that is imposed on the learner’s cognitive system when performing a particular learning task. One dimension is called *intrinsic load*. It includes the demands on working memory capacity imposed by the extent to which relevant elements of the learning material interact (Paas, Renkl, & Sweller, 2003). The manner in which information is presented to learners and the learning activities of learners can also impose a cognitive load. When that load is unnecessary with respect to learning, it is referred to as *extraneous load*. *Germane load* results in those resources devoted to learning.

In the case of relating aids such as color codes, corresponding surface features serve as indicators for the relations between corresponding parts in different representations (Kalyuga, Chandler, & Sweller, 1999; see also Ayres & Sweller, 2005; Renkl, 2005: easy-mapping principle). Thereby, visual search processes that do not contribute to conceptual understanding can be reduced. In terms of cognitive load theory, extraneous load is decreased (cf. Paas, Renkl, & Sweller, 2003; Sweller, 2005). Color coding was successfully employed by Kalyuga, Chandler, and Sweller (1998). The learners’ attention was guided to relevant parts of both representations and relieved processing demands in working memory, which resulted in better learning outcomes (for similar results, see Folkers, Ritter, & Sichelschmidt; 2005; Jeung, Chandler, & Sweller, 1997; Kalyuga et al., 1999). Moreover, computer-based learning environments offer the possibility of flashing in order to help students relate the MERs (e.g., Mayer, 2005b). The learner’s attention is thereby also directed toward the corresponding parts in the different representations.

In essence, it seems promising to support learners in integrating MERs on a surface level by instructional techniques such as color coding or flashing. As a result, the need for learners to engage in visual search processes is reduced and extraneous load is lowered. However, making salient which elements correspond does not ensure that the MERs are also integrated on a structural level, which helps in gaining conceptual understanding.

**Supporting Integration on a Structural Level by Self-Explanation Prompts**

In addition to instructional support procedures supporting the integration of MERs on a surface level, learners can be supported in integrating the corresponding aspects on a structural level (cf. Seufert & Brünken, 2004). Thereby, learners should be guided to try for conceptual integration of the MERs (abstraction function; Ainsworth, 2006; see also Ainsworth, 1999; Seufert & Brünken, 2006). Recently, Roy and Chi (2005) concluded on the basis of a review on prior studies that self-explanations should be especially suited to foster conceptual understanding when MERs have to be integrated at a higher level. However, a direct empirical test of the helpfulness of self-explanation prompts for integrating MERs is missing.

Self-explaining was extensively analyzed by Chi and her colleagues (for a summary, see Chi, 1997). According to Chi (2000), it refers to utterances in which participants explain the contents during learning to themselves; the *self* in self-explanation, thus, refers both to the agent who provides the explanation and, even more importantly, to the addressee of the explanation. The function of self-explanations is to actively make sense of the presented material (Chi, 2000). The directness of these types of explanations to oneself in particular distinguishes it from other constructive learning activities, such as explaining to another person (e.g., tutor or teacher; Chi, 2000; see also Roy & Chi, 2005). Whereas, in the beginning of self-explanation research, self-explanations were conceived as oral explanations, it is meanwhile also usual to regard written utterances as self-explanations as well (e.g., Hausmann & Chi, 2002; Große & Renkl, 2006, 2007; Schworm & Renkl, 2006, 2007).

Several cognitive mechanisms can be involved in self-explaining: generating inferences to fill in missing information, relating the problems’ surface features to structural features, integrating new information with prior knowledge, and repairing faulty knowledge (Roy & Chi, 2005). In terms of cognitive load theory, self-explanations correspond to germane load (Sweller et al., 1998; Renkl, 2005). Many studies have established the benefits of self-explaining with respect to learning processes and learning outcomes specifically in example-based learning (see Atkinson, Renkl, & Merrill, 2003; Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Renkl, 2005; Schworm & Renkl, 2007) but meanwhile also for other learning methods and across a variety of domains, different ranges of age, and learning contexts (Roy & Chi, 2005).

An instructional problem is that many learners do not spontaneously engage in effective self-explanation activities, that is, they do not productively use their free cognitive capacity in order to deepen their understanding (Renkl, 1997). This deficit is not primarily due to a lack of prior knowledge. Chi, de Leeuw, Chiu, and Lavancher (1994) and Ainsworth and Loizou (2003) found no relationship between the amount of self-explaining and prior knowledge. However, Conati and VanLehn (2000) showed that the level of assistance necessary for generating self-explanations varied with the student’s prior knowledge (for similar results, see Renkl, Stark, Gruber, & Mandl, 1998). A well-established approach of assistance is the use of self-explanation prompts. Prompts are questions or hints that induce productive learning processes. They are designed to overcome superficial processing because they induce learning strategies that the learners are, in principle, capable of, but do not spontaneously demonstrate, or demonstrate to an unsatisfactory degree (e.g., Pressley et al., 1992). Atkinson, Renkl, and Merrill (2003) showed that prompting principle-based self-explanations in a computer-based learning environment providing worked examples on probability led to...
favorable learning outcomes (for similar findings on self-explanation prompts in example-based learning, see Conati & VanLehn, 2000; Schworm & Renkl, 2006, 2007). Thus, not only are spontaneous self-explanations—as in the early years of self-explanation research (e.g., Renkl, 1997)—called self-explanations but also instructionally supported self-explanations (e.g., Atkinson, Renkl, & Merrill, 2003; Chi et al., 1994). In a nutshell, the focus is on explaining new knowledge to oneself and thereby actively making sense of the learning material (see Chi, 2000)—regardless of the level of provided instructional support (e.g., prompts).

However, even when self-explanations are prompted, their quality is, in many cases, far from optimal (Renkl, 2002; Roy & Chi, 2005). Often, the self-explanations are fragmented (Roy & Chi, 2005), only partially correct, or even incorrect (Renkl, 2002). This can lead to incomplete or incorrect knowledge. In contrast to this assumption, Chi (2000) stated that incorrect self-explanations are harmless or can even create an opportunity for cognitive conflicts that eventually lead to self-explanation episodes and conflict resolution (Chi et al., 1989; see VanLehn, 1999: impasse-driven learning). Although Conati and VanLehn (2000) believe, as Chi (2000), that even incorrect and incomplete self-explanations can improve learning, they argued that helping students generate more correct self-explanations can extend these benefits. The instructional method of scaffolding offers a promising starting point to optimize self-explanations. Scaffolding can be conceived as a support procedure that at the beginning relieves learners of parts of a task, which would be out of reach for learners without assistance (e.g., integrating MERs on a structural level) (Collins, Brown, & Newman, 1989). Berthold, Eysink, and Renkl (2008) compared the effects of three conditions when self-explaining multirepresentational worked examples from the domain of probability: scaffolding self-explanation prompts that directed the learners to integrate the MERs on a deep-structure level (i.e., fill-in-the-blank explanations followed by open self-explanation prompts), open self-explanation prompts (right from the beginning), and no self-explanation prompts. Both types of self-explanation prompts fostered procedural knowledge (i.e., problem-solving performance). However, conceptual knowledge (i.e., knowledge about the rationale of a solution procedure) was particularly fostered by scaffolding self-explanation prompts. The latter effect was mediated by self-explanations that not only relate a solution step to an underlying principle but also explicate the rationale of the principle (Berthold et al., 2008). Thus, especially for enhancing conceptual understanding, scaffolding self-explanation prompts are a sensible instructional support. We took up this finding in the present study and employed scaffolding self-explanation prompts.

Overview of the Experiment, Hypotheses, and Research Questions

MERs often do not provide the expected benefits, especially because the learners do not integrate the different representations (see Ainsworth et al., 1998, 2002; for an overview, see also Ainsworth, 2006). Hence, it seems sensible to instructionally support the integration and understanding of MERs. One support procedure is to design the learning materials in a way that helps the learners to figure out which elements in different representations correspond to each other. In addition, self-explanations prompts can be employed in order to ensure that learners integrate corresponding parts in different representations on a structural level, which deepens conceptual understanding.

In a nutshell, the first main goal of the present study was to test whether learners generally benefit from learning with MERs. To answer this question, we examined learning either with MERs (i.e., an arithmetical and a pictorial tree diagram) or with single representations (i.e., an arithmetical equation or a pictorial tree diagram). Our second main goal referred to analyzing the effects of instructional procedures that help learners integrate MERs in order to optimize learning.

In the present experiment, we employed the method of learning from worked examples because this instructional approach is known to impose relatively little working memory load (Renkl, Gruber, Weber, Lerche, & Schweizer, 2003; Sweller et al., 1998). Thus, more cognitive capacity is left for integrating MERs. We chose probability theory as the domain. In this domain, there are two types of typical solution methods: arithmetical solution (relying on a formula) and graphical solution in the form of a tree diagram.

More specifically, we tested the effects of multirepresentational versus monorepresentational example solutions, of a relating aid (a flashing-color-coding procedure), and of scaffolding self-explanation prompts (fill-in-the-blank explanations followed by open self-explanation prompts) on learning processes (i.e., self-explanations) and learning outcomes (i.e., conceptual knowledge and procedural knowledge). Conceptual knowledge referred to understanding-why knowledge about the rationale of a solution procedure (i.e., why is a solution procedure applied in a specific way). Procedural knowledge referred to problem-solving performance. Specifically, we tested the following hypotheses and research questions:

1. Multirepresentational solutions, a relating aid, and scaffolding self-explanation prompts foster conceptual knowledge.
   a. The form of representation of the solutions (pictorial, arithmetical, multirepresentational) influences the acquisition of conceptual knowledge. Scaffolding self-explanation prompts foster conceptual knowledge irrespective of the type of provided representation(s).
   b. When learning with multirepresentational solutions, a relating aid and scaffolding self-explanation prompts foster conceptual knowledge.

   a. The form of representation of the solutions (pictorial, arithmetical, multirepresentational) influences the acquisition of procedural knowledge. Scaffolding self-explanation prompts foster procedural knowledge irrespective of the type of provided representation(s).
   b. When learning with multirepresentational solutions, a relating aid and scaffolding self-explanation prompts foster procedural knowledge.
3. The type of representational examples (multi- vs. mono-), a relating aid, and scaffolding self-explanation prompts influence self-explanation activity.

   a. Does the form of representation of the solutions influence self-explanation activity? To what extent do scaffolding self-explanation prompts actually foster different types of self-explanations irrespective of the type of provided representation(s)?

   b. When learning with multirepresentational solutions, does a relating aid and scaffolding self-explanation prompts influence self-explanation activity?

4. The (potential) effects on conceptual knowledge and procedural knowledge are mediated by specific types of self-explanations.

5. The type of representational examples (multi- vs. mono-), a relating aid, and scaffolding self-explanation prompts influence subjective cognitive load during learning.

   a. Does the form of representation of the solutions influence subjective cognitive load during learning? Do scaffolding self-explanation prompts influence subjective cognitive load irrespective of the type of provided representation(s)?

   b. When learning with multirepresentational solutions, does a relating aid and scaffolding self-explanation prompts influence subjective cognitive load during learning?

Method

Sample and Design

The participants of this study were 87 female and 83 male students from grades 10 and 11 of German high schools (in German Gymnasiums). After primary school, German students have three different options for secondary schooling. Gymnasiums are the highest academic track in this three-track system. Students of the Gymnasium prepare for the Abitur, which is the exit exam that qualifies students for higher education. The mean age of the participants was 16.21 years (SD = .91). The participants received €7.50 per hour (~US$10).

In an experiment with eight conditions, four monorepresentational (pictorial or arithmetical representation) conditions and four multirepresentational (pictorial and arithmetical representation) conditions were implemented (see Table 1): (a) pictorial solutions/no self-explanation prompts, (b) pictorial solutions/self-explanation prompts, (c) arithmetical solutions/no self-explanation prompts, (d) arithmetical solutions/self-explanation prompts, (e) pictorial and arithmetical solutions/no relating aid/no self-explanation prompts, (f) pictorial and arithmetical solutions/no relating aid/self-explanation prompts, (g) pictorial and arithmetical solutions/relating aid/no self-explanation prompts, (h) pictorial and arithmetical solutions/relating aid/self-explanation prompts. The participants were randomly assigned to each of the eight conditions. It was not possible to implement a 3 (form of representation: pictorial, arithmetical, multirepresentational) × 2 (with vs. without self-explanation prompts) × 2 (with vs. without a relating aid) design because in the conditions with monorepresentational solutions (arithmetical and pictorial) a relating aid cannot be employed. Thus, the conditions were not fully crossed. Instead, we adopted two overlapping designs: (a) a 3 (form of representation: pictorial, arithmetical, multirepresentational) × 2 (with vs. without self-explanation prompts) design, which is represented by a boldface framework in Table 1 and (b) a 2 (with vs. without self-explanation prompts) × 2 (with vs. without a relating aid) design with respect to the four multirepresentational conditions, which is represented by gray shading in Table 1. The two multirepresentational conditions without relating aid overlap the two designs.

In the computer-based learning environment, all learners studied four pairs of isomorphic worked examples (i.e., eight examples in total). Worked examples consist of a problem formulation, solution steps, and the final solution itself. The learners did not receive any explanations about the provided solutions. In the multirepresentational conditions, the solution steps were provided in the form of both a pictorial tree diagram and an arithmetical equation in each example (see Figures 1 and 2). In the monorepresentational conditions, the learners received almost the same worked examples, including the problem formulation, the solution steps, and the final solution itself, as presented in Figure 2. The only difference was that the solution steps were presented in the form of a pictorial tree diagram or an arithmetical equation.

In two of the multirepresentational conditions, the learners were supported in integrating the arithmetical information (e.g., the multiplication signs) and the respective information from the tree diagram (e.g., the ramifications) by a relating aid (see Figure 1 for a version with a relating aid and see Figure 2 for a version without a relating aid). The relating aid included corresponding information from the different representations that was simultaneously flashing in the same color—information pair after information pair. At the end, a colored freeze image was presented.

Participants of the conditions with scaffolding self-explanation prompts received questions that were specifically designed to elicit self-explanations (e.g., “Why do you calculate the total acceptable outcomes by multiplying?”). In the first worked example of each pair of isomorphic examples, the answers were supported by a

### Table 1

<table>
<thead>
<tr>
<th>Group</th>
<th>Scaffolding prompts</th>
<th>No self-explanation prompts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pictorial solutions</td>
<td>n = 21</td>
<td>n = 21</td>
</tr>
<tr>
<td>Arithmetical solutions</td>
<td>n = 21</td>
<td>n = 22</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and</td>
<td>n = 21</td>
<td>n = 22</td>
</tr>
<tr>
<td>arithmetical) solutions/no relating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>aid</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multirepresentational (pictorial and</td>
<td>n = 21</td>
<td>n = 21</td>
</tr>
<tr>
<td>arithmetical) solutions/relating aid</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. The boldface framework represents a 3 (form of representation) × 2 (with vs. without self-explanation prompts) design; the gray shaded condition represents a 2 (with vs. without self-explanation prompts) × 2 (with vs. without a relating aid) design.
Learning Environment

Probability theory (specifically: complex events) was chosen as the learning domain because it is suitable for the use of different representation codes (pictorial and arithmetical). In addition, it is relatively difficult for learners. The computer-based learning environment included eight worked examples. The participants were allowed to regulate the processing speed of the worked examples on their own.

In the worked examples, four principles were addressed that are to be applied when determining probabilities in the cases of (a) order relevant, (b) order irrelevant, (c) without replacement, and (d) with replacement. The principles were instantiated by four pairs of isomorphic worked examples. In each example pair, the application of one of the following principle combinations was demonstrated: (a) order relevant—without replacement, (b) order relevant—with replacement, (c) order irrelevant—without replacement, and (d) order irrelevant—with replacement.

One special focus of our learning environment was on the understanding of the multiplication rule. This rule is central when calculating the probabilities of complex events. Usually, the learners understand that the multiplication rule has to be applied, but they rarely understand why the fractions have to be multiplied. For many learners, the latter is not apparent. However, it is encapsulated in the multirepresentational solution. The learner can unpack it by integrating the information of the multiplication sign of the arithmetical code with the ramifications in the tree diagram (e.g., for the denominator there are five times four branches). Thereby, the learners can understand that the ramifications in the tree diagram represent “multiplication,” and they can realize that this multiplication includes all possible combinations, which are depicted, for example, by the five times four branches in the tree diagram (see Figure 1).
Procedure

This experiment was conducted in group sessions. The learners worked individually in front of a computer screen. First, the participants were asked to fill out a questionnaire on demographic data. Afterwards, the learners worked on a pretest. Next, they entered the learning environment. In order to provide or reactivate basic knowledge that allowed the participants to understand the following worked examples, we provided an instructional text on basic principles of probability. Afterwards, the participants studied eight worked examples. During this phase, the experimental manipulation was realized. After every other worked example, participants were asked to answer five questions on subjective cognitive load. Finally, they completed a posttest on procedural knowledge and conceptual knowledge.

Instruments

Pretest: Assessment of prior knowledge. A pretest on complex events with 12 items examined the prior knowledge with respect to the topic probability theory. It included 4 simple items that assessed basic knowledge of probability theory (e.g., “You are playing a game with a die, and it is your turn to throw. If you throw a 3, you win. What is the probability that you will throw a 3?”). In addition, eight multiple-choice items and calculation items were included (e.g., “Your Latin teacher draws lots for two students in the Latin course [altogether 7 students] who are supposed to read aloud their translation. Unfortunately, you have copied it from your friend. What is the probability that the two of you will be selected?”). The items were scored by 0 points (incorrect answer) or by 1 point (correct answer). In total, 12 points could be achieved. This sum was divided by the number of items (12) so that the test score represented the proportion of items solved correctly.

Self-explanations: Assessment of learning processes. In all conditions, the written responses to the prompts or the annotations in the text boxes (in the no-prompts conditions), respectively, were analyzed. The quality of written self-explanations is a good indicator of the quality of the learning processes (e.g., Schworm & Renkl, 2006). Similar as in Berthold et al. (2008), the protocols were thoroughly examined for content segments that corresponded to the following self-explanation categories (Roy & Chi, 2005):

(a) Principle-based self-explanations. A learner assigns meaning to a solution step by identifying the underlying domain principles (e.g., “order relevant, with replacement”). This activity fosters a principle-based understanding of solution procedures (see Renkl, 2005). The number of times that participants referred to principles was counted. However, if a principle was merely mentioned without any elaboration (e.g., “order relevant”), this category was not scored. There had to be some elaboration of a principle (e.g., “The order is relevant because it does matter in which order you type in the numbers of a PIN”). This category corresponds to Chi et al.’s (1989) category of references to Newton’s Laws (the underlying domain principles in that study).

(b) Rationale-based self-explanations. This category refers to self-explanations about the rationale of a principle (see Berthold et al., 2008). Rationale-based self-explanations exceed principle-based self-explanations by giving reasons as to why the principle is as it is. For instance, it was not sufficient to merely state that one has to multiply, but the learners also had to explain why one has to multiply. In other words, the rationale behind the principle must be provided. A rationale-based self-explanation on the open prompt, “Why do you calculate the total acceptable outcomes by multiplying?” is the following: “For the denominator, there are five times four branches. Thus, each of the five first branches of the tree diagram forks out in four further branches because each of the five first events can occur in combination of one of the four remaining events.” To provide such a self-explanation, it was helpful to integrate the multiplication sign of the arithmetical equation with the ramifications of the pictorial tree diagram.

(c) Incorrect self-explanations in terms of confusion of principles. This category was scored if the learner generated an incorrect self-explanation that reflected systematic misunderstandings in terms of confusion of principles (e.g., confusion of the principles “order relevant” and “order irrelevant,” confusion of the principles “without replacement” and “with replacement,” or confusion of the principles “order” and “replacement”). This category was not scored if the learners generated slips of the pen or made calculation errors. Hence, only systematic misunderstandings with respect to underlying domain principles were scored as incorrect self-explanations and not errors, which were not associated with the primary learning goals of the learning environment.

The coding categories were distinct. In the conditions with scaffolding self-explanation prompts, the learners filled in the scaffolds in the first worked example of each pair, whereas the learners of the conditions without prompts simply took notes. The later statistical analyses only refer to the written responses to the prompts or to the annotations in the text boxes of every second isomorphic example in order to assure comparability between conditions (i.e., in all conditions, empty boxes had to be filled out in the second isomorphic examples).

The written self-explanations of 33 participants (20.63% of the assessed self-explanations) were coded by a student research assistant and Kirsten Berthold. During coding the raters were blind to the experimental conditions and study hypotheses. Interrater reliability with respect to assigning the protocol segments to the coding categories was very good (Cohen’s κ = .82). In case of divergence, Kirsten Berthold reexamined the protocols and made the final decision. As the interrater reliability was very good (see Fleiss & Cohen, 1973), the rest of the protocols were coded by just one rater. Due to technical problems, the process data sets of 10 participants were lost (2 from the groups “arithmetical solutions/no self-explanation prompts” and “pictorial and arithmetical solutions/no relating aid/no self-explanation prompts,” respectively, as well as one data set of each of the other groups).

Cognitive load questions: Assessment of subjective cognitive load. After every second isomorphic example, the learners were asked to answer five questions on various aspects of subjective cognitive load on a 9-point rating scale (1 = lowest score, 9 = highest score). In their literature review, Paas, Tuovinen, et al. (2003) provided evidence for the usefulness of such subjective questions in assessing cognitive load and emphasized that it is frequently used in current cognitive load research. The questions were related to intrinsic load, extraneous load, and germane load (see Table 2). The set of items was an adapted and extended version of the SOS scale (Subject matter difficulty, Operating the system, and usability of Support tools; Swaak & de Jong, 2001). The order in which the items within the sets were presented
differed each time to prevent learners from answering automatically. For the later analyses, the scores of the five questions after every second of the eight examples (totally 20 questions) were aggregated (Cronbach’s α = .95).

Posttest: Assessment of learning outcomes. The posttest contained 23 problems. Most of these problems were more difficult than the pretest items. All items were scored by 0 points (incorrect answer) or 1 point (correct answer). The posttest assessed the following knowledge types.

Procedural knowledge (problem-solving performance) referred to actions or manipulations that are valid within a domain, for example, multiplying two fractions to calculate the probability of a complex event (see de Jong & Ferguson-Hessler, 1996). This category included two open questions, 11 near-transfer items (same structure as the worked examples presented for learning but different surface features, such as the cover story), and four far-transfer items (different surface features and also different structures, which meant that a modified solution procedure had to be found). An example of an open question is

The children’s play pens at IKEA [a furniture store] contain balls in different colors among which are red, yellow, green, and orange. Please describe, in your own words, how you would determine the probability that a blindfolded child will pick a red ball, then a green one, followed by a yellow, and an orange ball.

An example for a near-transfer item is

You spin a wheel of fortune twice. The wheel has nine corresponding segments with different pictures (among which are a cloverleaf and a pig). You win if you once hit the segment cloverleaf and the other time the segment pig. What is the probability that you win?

An example for a far-transfer item is

Eight drivers of different sports clubs (A, B, C, D, E, F, G, and H) take part in a soapbox derby. The winner receives 100 euro, the driver in second place gets 50 euro, and third place gets 25 euro. The drivers of the soapbox karts that finish fourth and fifth get consolation prices in the form of tickets for hot springs. You make a bet with your brother, that the driver of the Sports Club D will win 100 euro, the driver of the Sports Club H 50 euro, the one of Sports Club E 25 euro, and the drivers of the Sports Clubs A and B the consolation prizes. What is the probability that you win your bet?

Since no different patterns of results were found for the different subscores, they were pooled together. In total, 17 points could be achieved. This sum was divided by the number of items (17) so that the test score represented the proportion of items solved correctly. The results of the transfer items \(M = 0.44, SD = 0.21\) were not influenced by floor or ceiling effects. None of the participants scored zero points.

Conceptual knowledge referred to knowledge about facts, concepts, and principles that apply within a domain (de Jong & Ferguson-Hessler, 1996). We focused especially on understanding why the solution procedures are as they are. Thus, it included conceptual understanding about what is behind the solution procedure. This category contained six open questions, which required written explanations on the principles presented in the learning phase. For example, the learners were to explain why fractions have to be multiplied (e.g., “Why are the two fractions multiplied and not added?”). As the rationale for the multiplication rule can be figured out relatively easily when the pictorial and the arithmetical representations are integrated, this posttest measure also touched on the quality of representation integration. A coding system of the LEMMA (Learning Environments, MultiMedia, and Affordances) cooperation project was used. Members of this cooperation project were four research groups that used common tests and coding systems for these tests in their experiments. The coding system was kept clear and simple. One point was assigned for a correct answer with a substantial degree of reasoning and elaboration. The LEMMA coding system provided examples for correct examples that were based on a prestudy. Other answers were scored with zero points. For such incorrect answers, the LEMMA coding system provided several example answers that were also based on the prestudy. Interrater reliability for this coding system was very good (Cohen’s κ = .95). On the whole, 6 points could be achieved. This sum was divided by the number of items (six) so that the test score represented the proportion of items solved correctly.

**Results**

An alpha level of .05 was used for all statistical analyses. As an effect size measure, we used (partial) \(\eta^2\) qualifying values < .06 as small effects, values in the range between .06 and .13 as medium effects, and values > .13 as strong effects (see Cohen, 1988).

With respect to the learners’ prior knowledge (see Table 3), a 3 (form of representation: pictorial, arithmetical, multirepresentational) × 2 (with and without self-explanation prompts) factorial analysis of variance on the prior knowledge revealed neither significant main effects for the form of representation, \(F(2, 121) = 1.47, p = .233\), and for scaffolding self-explanation prompts, \(F(1, 121) = 3.00, p = .086\), nor a significant interaction between form of representation and scaffolding self-explanation prompts \(F < 1\). Similarly, a 2 × 2 analysis of variance, with the factors relating aid and scaffolding self-explanation prompts, yielded neither significant main effects nor a significant interaction (all \(F < 1\)). Nevertheless, we included prior knowledge as covariate in subsequent analyses in order to reduce error variance.
Effects on Conceptual Knowledge

Hypothesis 1a stated that the form of representation of the solutions (pictorial, arithmetical, or multirepresentational) influences the acquisition of conceptual knowledge and that scaffolding self-explanation prompts foster conceptual knowledge irrespective of the type of provided representation(s). A 3 (form of representation: pictorial, arithmetical, multirepresentational) × 2 (with vs. without self-explanation prompts) factorial analysis of covariance (ANCOVA) revealed a non significant main effect of the form of representation, $F(2, 120) = 2.32$, $p = .103$ (see Table 4). However, there was a main effect for scaffolding self-explanation prompts, $F(1, 120) = 20.88$, $MSE = .03$, $p < .001$, $\eta^2 = .15$; self-explanation prompts fostered conceptual knowledge. The interaction between form of representation and self-explanation prompts did not reach the level of significance ($F < 1$).

Hypothesis 1b stated that when learning with multirepresentational solutions, a relating aid and scaffolding self-explanation prompts foster conceptual knowledge. To test this hypothesis, we conducted a $2 \times 2$ factorial ANCOVA (prior knowledge was included as a covariate) to analyze the multirepresentational groups as a $2 \times 2$ design (with and without a relating aid; with and without self-explanation prompts). We found a significant main effect for the relating aid, $F(1, 80) = 5.75$, $p = .019$, $\eta^2 = .07$, as well as for the scaffolding self-explanation prompts, $F(1, 80) = 15.09$, $MSE = .04$, $p < .001$, $\eta^2 = .16$; both instructional procedures fostered conceptual knowledge. The interaction between relating aid and self-explanation prompts did not reach the level of significance ($F < 1$). Thus, scaffolding self-explanation prompts and a relating aid had an additive effect on the acquisition of conceptual knowledge.

In sum, conceptual knowledge was fostered by scaffolding self-explanation prompts whatever (combination of) representation(s) were employed. In the case of MERs, the relating aid also led to deeper conceptual understanding. These findings corresponded to our hypotheses. Contrary to our expectations, the form of representation of the solutions did not influence the acquisition of conceptual knowledge.

**Effects on Procedural Knowledge**

We assumed that the form of representation of the solution(s) (i.e., pictorial, arithmetical, or multirepresentational) influences the acquisition of procedural knowledge and that scaffolding self-explanation prompts foster procedural knowledge irrespective of the type of provided representation(s). A $3 \times 2$ ANCOVA yielded a significant main effect of the form of representation, $F(2, 120) = 3.31$, $MSE = .029$, $p = .040$, $\eta^2 = .05$ (see Table 4). An inspection of the mean scores in Table 4 suggested that participants who learned with arithmetical solutions acquired more procedural knowledge. We contrasted—using the Bonferroni procedure for posteriori contrasts—the groups with arithmetical solutions against the groups with multirepresentational solutions and pictorial solutions. This contrast revealed that learning with arithmetical solutions ($M = .46, SD = .19$) was significantly more helpful with respect to the acquisition of procedural knowledge than learning with multirepresentational ($M = .42, SD = .21$) or pictorial solutions ($M = .40, SD = .19$), $F(1, 120) = 6.43$, $p = .012$, $\eta^2 = .05$ (Bonferroni-corrected $\alpha = .017$). There was neither a significant effect in favor of the groups with multirepresentational solutions when compared to the groups with pictorial or arithmetical solutions.

Table 3
**Means and Standard Deviations (in Parentheses) of the Pretest Measure**

<table>
<thead>
<tr>
<th>Group</th>
<th>Prior knowledge</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scaffolding self-explanation prompts</td>
</tr>
<tr>
<td>Pictorial solutions</td>
<td>.41 (.21)</td>
</tr>
<tr>
<td>Arithmetical solutions</td>
<td>.33 (.16)</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and arithmetical) solutions/no relating aid</td>
<td>.44 (.19)</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and arithmetical) solutions/relating aid</td>
<td>.46 (.19)</td>
</tr>
</tbody>
</table>

Note. The boldface framework represents a 3 (form of representation) × 2 (with vs. without self-explanation prompts) design; the gray shaded condition represents a 2 (with vs. without self-explanation prompts) × 2 (with vs. without a relating aid) design.

Table 4
**Means and Standard Deviations (in Parentheses) of the Posttest Measures**

<table>
<thead>
<tr>
<th>Group</th>
<th>Conceptual knowledge</th>
<th>Procedural knowledge</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scaffolding self-explanation prompts</td>
<td>No self-explanation prompts</td>
</tr>
<tr>
<td>Pictorial solutions</td>
<td>.40 (.19)</td>
<td>.29 (.17)</td>
</tr>
<tr>
<td>Arithmetical solutions</td>
<td>.45 (.21)</td>
<td>.36 (.17)</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and arithmetical) solutions/no relating aid</td>
<td>.48 (.17)</td>
<td>.33 (.18)</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and arithmetical) solutions/relating aid</td>
<td>.59 (.19)</td>
<td>.41 (.23)</td>
</tr>
</tbody>
</table>

Note. The boldface framework represents a 3 (form of representation) × 2 (with vs. without self-explanation prompts) design; the gray shaded condition represents a 2 (with vs. without self-explanation prompts) × 2 (with vs. without a relating aid) design.
ical solutions (F < 1) nor for the groups with pictorial solutions when compared to the groups with arithmetical or multirepresentational solutions, F(1, 120) = 2.75, p = .100.

With respect to the scaffolding self-explanation prompts, we obtained a significant effect, F(1, 120) = 5.48, p = .021, η² = .04. However, the latter effect was a negative effect, that is, the prompts impeded the acquisition of procedural knowledge. There was no significant interaction effect of the form of representation and the scaffolding self-explanation prompts (F < 1). Hence, the effects of the two instructional variations did not depend on each other.

Hypothesis 2b stated that when learning with multirepresentational solutions, a relating aid and scaffolding self-explanation prompts foster procedural knowledge. Both the main effects (for the relating aid: F[1, 80] = 2.41, MSE = .033, p < .124; for the scaffolding self-explanation prompts: F[1, 80] = 2.46, p = .121) and the interaction effect, F(1, 80) = 2.14, p = .147, of the 2 × 2 factorial ANCOVA failed to reach the level of statistical significance.

In sum, the form of representation influences the acquisition of procedural knowledge. A posteriori contrasts revealed that arithmetical solutions were most effective with respect to the acquisition of procedural knowledge irrespective of the type of provided representation.

Effects on Self-Explanations

Note again that only the written self-explanations in the text boxes of every second isomorph example were analyzed for reasons of comparability across conditions (empty text boxes in each condition—no fill-in-the-blank texts in the conditions with scaffolding self-explanation prompts). Research Question 3a asked whether the form of representation influences self-explanation activity, and to what extent scaffolding self-explanation prompts actually foster different types of self-explanations irrespective of the type of provided representation(s). With respect to Research Question 3b, we analyzed whether a relating aid for multiple representations influences self-explanation activity and to what degree self-explanation prompts impeded the acquisition of procedural knowledge. There was no significant interaction effect of the form of representation and the scaffolding self-explanation prompts (F < 1). Hence, the effects of the two instructional variations did not depend on each other.

Hypothesis 2b stated that when learning with multirepresentational solutions, a relating aid and scaffolding self-explanation prompts foster procedural knowledge. Both the main effects (for the relating aid: F[1, 80] = 2.41, MSE = .033, p < .124; for the scaffolding self-explanation prompts: F[1, 80] = 2.46, p = .121) and the interaction effect, F(1, 80) = 2.14, p = .147, of the 2 × 2 factorial ANCOVA failed to reach the level of statistical significance.

In sum, the form of representation influences the acquisition of procedural knowledge. A posteriori contrasts revealed that arithmetical solutions were most effective with respect to the acquisition of procedural knowledge irrespective of the type of provided representation.

Effects on principle-based self-explanations. A 3 × 2 factorial ANCOVA, with the factors form of representation and scaffolding self-explanation prompts, revealed no significant main effect with respect to the form of representation (F < 1). However, there was a significant main effect for the scaffolding self-explanation prompts, F(1, 112) = 333.89, MSE = 2.72, p < .001, η² = .75 (see also Table 5). The interaction effect was not significant (F < 1). Similarly, a 2 × 2 ANCOVA, with the factors relating aid and scaffolding self-explanation prompts, yielded again a significant main effect for the scaffolding self-explanation prompts, F(1, 75) = 217.10, MSE = 2.52, p < .001, η² = .74. There was neither a significant main effect for the relating aid (F < 1) nor a significant interaction effect, F(1, 75) = 1.47, p = .230.

Effects on rationale-based self-explanations. Consistent with the previous results regarding principle-based self-explanations, we found a significant main effect for the scaffolding self-explanation prompts in a 3 × 2 factorial ANCOVA, F(1, 112) = 44.08, MSE = 3.97, p < .001, η² = .28 (see also Table 5), whereas the main effect for the form of representation and the interaction effect again did not reach the level of statistical significance (both Fs < 1). In a 2 × 2 ANCOVA, we obtained a significant main effect in favor of the scaffolding self-explanation prompts groups, F(1, 75) = 35.91, MSE = 5.20, p < .001, η² = .32. The main effect for the relating aid and the interaction effect did not reach the level of statistical significance, F(1, 75) = 1.57, p = .214, and F < 1.

Effects on incorrect self-explanations in terms of confusion of principles. A 3 × 2 factorial ANCOVA yielded a significant main effect of the scaffolding self-explanation prompts, F(1, 112) = 72.02, MSE = .88, p < .001, η² = .40 (see also Table 5), indicating that prompts led to more frequent confusions of principles, even when the level of prior knowledge is controlled for. The main effect for the form of representation and the interaction effect again did not reach the level of statistical significance (both Fs < 1).

When considering the MERs groups as a 2 × 2 design, we obtained a significant main effect of the scaffolding self-explanation prompts, F(1, 75) = 57.66, MSE = .83, p < .001,

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scaffolding self-explanation prompts</td>
<td>No self-explanation prompts</td>
<td>Scaffolding self-explanation prompts</td>
</tr>
<tr>
<td>Pictorial solutions</td>
<td>5.50 (2.19)</td>
<td>.50 (1.57)</td>
<td>2.60 (2.91)</td>
</tr>
<tr>
<td>Arithmetical solutions</td>
<td>5.60 (2.52)</td>
<td>.15 (.37)</td>
<td>1.85 (2.16)</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and arithmetical solutions/no relating aid)</td>
<td>4.70 (3.03)</td>
<td>.15 (.37)</td>
<td>2.60 (3.30)</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and arithmetical solutions/relating aid)</td>
<td>4.90 (2.53)</td>
<td>.25 (.64)</td>
<td>3.70 (3.20)</td>
</tr>
</tbody>
</table>

Note. The boldface framework represents a 3 (form of representation) × 2 (with vs. without self-explanation prompts) design; the gray shaded condition represents a 2 (with vs. without self-explanation prompts) × 2 (with vs. without a relating aid) design.
Thus, the prompts led again more frequently to incorrect self-explanations in terms of confusions of principles. The main effect for the relating aid and the interaction effect between relating aid and self-explanation prompts were not significant (both F < 1).

In sum, scaffolding self-explanation prompts fostered rationale-based self-explanations as well as principle-based self-explanations. However, they also evoked more incorrect self-explanations in terms of confusion of principles. More specifically, learners who were provided scaffolding self-explanation prompts more frequently confused mathematical principles than their counterparts who were not provided such prompts. The form of representation and the relating aid did not influence self-explanation activity.

Mediation of the Effects on Conceptual Knowledge and Procedural Knowledge by Self-Explanations

Before testing the mediation effects, we determined the intercorrelations of the self-explanation variables as well as those between the learning outcome measures (i.e., conceptual knowledge and procedural knowledge).

Rationale-based self-explanations and principle-based self-explanations were substantially intercorrelated (.56; see Table 6). The correlations between rationale-based self-explanations and incorrect self-explanations in terms of confusion of principles (.19) as well as the correlations between principle-based self-explanations and incorrect self-explanations in terms of confusion of principles (.29) were lower but still significant (see Table 6). With respect to learning outcomes, we found significant correlations between conceptual knowledge and procedural knowledge (.28; see Table 6).

In the preceding sections, we established that self-explanation prompts evoked rationale-based and principle-based self-explanations but also produced incorrect self-explanations in terms of confusion of principles and the fact that they fostered conceptual knowledge but hindered the acquisition of procedural knowledge. Did the different types of self-explanations mediate the effects on conceptual and procedural knowledge? The pattern of results obtained so far would suggest that conceptual knowledge was fostered via rationale-based self-explanations and principle-based self-explanations and that procedural knowledge was hindered via incorrect self-explanations in terms of confusion of principles. Hence, we address the following questions: (a) Can the effects on conceptual knowledge be explained by rationale-based self-explanations and principle-based self-explanations? (b) Can the effects on procedural knowledge be explained by incorrect self-explanations in terms of confusion of principles?

(a) First, we addressed the question if the effects on conceptual knowledge can be explained by rationale-based self-explanations and principle-based self-explanations. We found significant correlations between rationale-based self-explanations and conceptual knowledge (.43) as well as between principle-based self-explanations and conceptual knowledge (.39; see Table 6). These latter correlations further supported the assumption of mediation of rationale-based self-explanations and principle-based self-explanations on conceptual knowledge.

We first directly tested whether in the 3 × 2 design rationale-based self-explanations mediated the effect of the independent variable prompts (scaffolding self-explanation prompts vs. no prompts) on conceptual knowledge. Therefore, three regression equations were estimated and tested for significance following the procedures suggested by Baron and Kenny (1986) and MacKinnon (2002). In order to establish mediation, (a) the independent variable (i.e., prompts) must affect the dependent variable (i.e., conceptual knowledge), (b) the independent variable (i.e., prompts) must affect the potential mediator (i.e., rationale-based self-explanations), and (c) the effect of the independent variable on the dependent variable should be significantly reduced when the mediator is included as an additional predictor of the dependent variable (cf. MacKinnon, 2002). First, prompts accounted for 22% of the variance in conceptual knowledge (21% adjusted), F(2, 124) = 17.22, p < .001. The second analysis demonstrated that the independent variable prompts affected rationale-based self-explanations, F(2, 116) = 23.21, p < .001; it accounted for 29% (27% adjusted) of the variance in the rationale-based self-explanations. The mediation hypotheses would have been supported if the effect of the independent variable prompts was substantially reduced when the mediator rationale-based self-explanations was included as an additional predictor of the dependent variable (cf. MacKinnon, 2002). Thus, in the third regression analysis, conceptual knowledge was regressed on the factor prompts and the mediator rationale-based self-explanations in a simultaneous multiple regression model. This regression equation accounted for 28% of the variance (26% adjusted), F(3, 115) = 14.07, p < .001. As expected, rationale-based self-explanations still significantly predicted conceptual knowledge, β = .28, t(114) = 3.02, p = .003. However, the effect of the factor prompts was still significant, β = .20, t(114) = 2.12, p = .036. In order to directly test whether rationale-based self-explanations in fact mediated the effect of the prompts on conceptual knowledge (i.e., whether the effect of the independent variable prompts was significantly reduced when the mediator rationale-based self-explanations was additionally included), we used the test procedure of MacKinnon (2002; see also MacKinnon & Dwyer, 1993).

This procedure included the computation of two regression equations: Mediator = (a × Independent) + error, and Dependent = (c × Independent) + (b × Mediator) + error. The mediation effect is defined as the product of the regression weights a and b, that is, the effect of the independent variable on the mediator multiplied by the effect of the mediator on the dependent variable when the independent variable is controlled. The statistical significance of the mediation effect is determined as follows: z = (a × b)/SE_{ab}, with SE_{ab} being the standard error of the mediation effect a × b, SE_{ab} = √{[(a^2 × (SE_a)^2) + (b^2 × (SE_b)^2)]} (cf. Sobel,

Table 6

<table>
<thead>
<tr>
<th>Self-explanation</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Principle-based self-explanations</td>
<td>.56**</td>
<td>.29**</td>
<td>.39**</td>
<td>.01</td>
<td></td>
</tr>
<tr>
<td>2. Rationale-based self-explanations</td>
<td>.19</td>
<td>.43**</td>
<td>.17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Incorrect self-explanations</td>
<td></td>
<td>.02</td>
<td>.29**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Conceptual knowledge</td>
<td></td>
<td></td>
<td>.28**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Procedural knowledge</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p < .05. **p < .01.
In such an analysis, we obtained a $z$ score of 2.74 that was significant on the 1% level. This finding indicated that the effect of the prompts on conceptual knowledge was significantly mediated by the number of rationale-based self-explanations. Thus, the prompts fostered conceptual knowledge because they effectively supported the learners in generating rationale-based self-explanations.

In addition to the mediation analysis according to the $3 \times 2$ design, we also conducted a corresponding mediation analysis according to the $2 \times 2$ design. Thus, we tested whether rationale-based self-explanations mediated the effect of the independent variable prompts on conceptual knowledge in the multiple representations. Therefore, three further regression equations were estimated and tested for significance. The first analysis demonstrated that scaffolding self-explanation prompts accounted for 21% of the variance in conceptual knowledge ($19\%$ adjusted), $F(2, 82) = 10.61, p < .001$. A second analysis showed that the independent variable prompts significantly affected the potential mediator (i.e., rationale-based self-explanations). This regression equation accounted for 34% of the variance ($32\%$ adjusted), $F(2, 77) = 19.73, p < .001$. Third, we tested whether the effect of the independent variable (prompts) on the dependent variable (conceptual knowledge) was clearly reduced when the mediator (rationale-based self-explanations) was included as an additional predictor of the dependent variable. The regression equation including prompts and rationale-based self-explanations as predictors accounted for 27% of the variance ($24\%$ adjusted), $F(3, 76) = 9.24, p < .001$. As expected, rationale-based self-explanations significantly predicted conceptual knowledge, $\beta = .35, t(75) = 2.86, p = .005$, whereas the effect of the factor prompts was no longer significant, $\beta = .18, t(75) = 1.51, p = .135$. In the mediation analysis according to MacKinnon (2002), we directly tested whether the effect of the independent variable prompts was significantly reduced when the mediator (rationale-based self-explanations) was additionally included. In this analysis, we obtained a $z$ score of 2.68 that was significant on the 1% level. Thus, the rationale-based self-explanations also mediated the impact of the scaffolding prompts on conceptual knowledge in the $2 \times 2$ design. In a nutshell, our findings suggest that the scaffolding self-explanation prompts fostered conceptual knowledge because the scaffolding self-explanation prompts effectively supported the learners in generating rationale-based self-explanations.

Furthermore, we tested whether principle-based self-explanations also mediated the effect of the independent variable prompts (scaffolding self-explanation prompts vs. no prompts) on conceptual knowledge in our $3 \times 2$ design. In the first regression analysis, conceptual knowledge was regressed on the factor prompts. Prompts accounted for 22% of the variance in the scores of conceptual knowledge ($21\%$ adjusted), $F(2, 124) = 17.22, p < .001$. The second regression analysis demonstrated the effect of the independent variable prompts on principle-based self-explanations, $F(2, 116) = 171.45, p < .001$; it accounted for 75% ($74\%$ adjusted) of the variance in the principle-based self-explanations. In the third regression analysis, conceptual knowledge was regressed on the factor prompts and principle-based self-explanations in a simultaneous multiple regression model. This regression equation accounted for 26% of the variance ($24\%$ adjusted), $F(3, 115) = 13.99, p < .001$. As to be expected, in the case of mediation, in this simultaneous regression model principle-based self-explanations still predicted conceptual knowledge, $\beta = .44, t(114) = 2.75, p = .007$, whereas the effect of the factor prompts was no longer significant, $\beta = -.029, t(114) = -.18, p = .858$. The procedure of MacKinnon (2002) yielded a $z$ score of 2.85 that was significant on the 1% level. Thus, not only rationale-based self-explanations but also principle-based self-explanations were a crucial mediator with respect to conceptual knowledge.

Additionally, we conducted a mediation analysis according to the $2 \times 2$ design. First, scaffolding self-explanation prompts accounted for 21% of the variance in conceptual knowledge ($19\%$ adjusted), $F(2, 82) = 10.61, p < .001$ (see above). The second regression analysis revealed a clearly significant effect of the independent variable prompts on principle-based self-explanations, $F(2, 77) = 113.01, p < .001$. However, in the third regression analysis, in which the factor prompts and principle-based self-explanations were regressed on conceptual knowledge, the effect of the principle-based self-explanations on conceptual knowledge was no longer significant, $\beta = .15, t(75) = .75, p = .457$. Therefore, the prerequisite for conducting the test procedure according to MacKinnon (2002), in order to directly test for mediation, was not accomplished.

In order to analyze whether both rationale-based self-explanations and principle-based self-explanations contributed independently to the mediation effect on conceptual knowledge, we included both rationale-based self-explanations and principle-based self-explanations as mediators in a simultaneous regression model (according to the $3 \times 2$ design). In this analysis, rationale-based self-explanations, $\beta = .25, t(113) = 2.69, p = .008$, and principle-based self-explanations, $\beta = .38, t(113) = 2.40, p = .018$, still significantly predicted conceptual knowledge, whereas the effect of the factor prompts was no longer significant, $\beta = -.11, t(113) = -0.68, p = .496$. In the procedure of MacKinnon (2002), a $z$ score of 2.45 that was significant on the 5% alpha level resulted. Thus, the effect on conceptual knowledge was mediated by both rationale-based self-explanations and principle-based self-explanations. The corresponding mediation analysis with respect to the $2 \times 2$ design failed to reach the level of statistical significance; in the simultaneous regression model, rationale-based self-explanations still significantly predicted conceptual knowledge, $\beta = .34, t(74) = 2.73, p = .008$, but the effect of principle-based self-explanations was not significant, $\beta = .012, t(74) = .061, p = .952$. Therefore, the prerequisite for conducting the test procedure according to MacKinnon (2002), in order to directly test for mediation of both rationale-based and principle-based self-explanations, was not accomplished.

(b) Secondly, we addressed the question whether the effects on procedural knowledge can be explained by incorrect self-explanations in terms of confusion of principles, that is, whether the incorrect self-explanations in terms of confusion of principles mediated the (negative) effects on procedural knowledge. We found that incorrect self-explanations in terms of confusion of principles and procedural knowledge were significantly correlated ($r = -.29$; see Table 6). This finding—in addition to the significant effect of scaffolding self-explanation prompts on incorrect self-explanations in the $3 \times 2$ model as well as in the $2 \times 2$ model and on hindering the acquisition of procedural knowledge in the $3 \times 2$ model—supported the assumption of the mediation of the incorrect self-explanations in terms of confusion of principles on procedural knowledge.
Thus, we estimated three regression equations according to the 3 × 2 design. The first analysis demonstrated that the type of prompts (scaffolding prompts vs. no prompts) accounted for 26% of the variance in procedural knowledge (25% adjusted), F(2, 124) = 21.93, p < .001. A second analysis showed that the independent variable (scaffolding prompts vs. no prompts) significantly affected the potential mediator (i.e., incorrect self-explanations in terms of confusion of principles). This regression equation accounted for 43% of the variance (42% adjusted), F(2, 116) = 44.39, p < .001. Third, we tested whether the effect of the independent variable (scaffolding prompts vs. no prompts) on the dependent variable (procedural knowledge) was reduced when the mediator (incorrect self-explanations in terms of confusion of principles) was included as an additional predictor of the dependent variable. The regression equation including prompts and incorrect self-explanations in terms of confusion of principles as predictors accounted for 29% of the variance (27% adjusted), F(3, 115) = 15.82, p < .001. As expected, the incorrect self-explanations still predicted procedural knowledge, β = −.22, t(114) = −2.07, p = .040, whereas the effect of the factor prompts was no longer significant, β = −.05, t(114) = −.477, p = .634. Following the procedure by MacKinnon (2002), a z score of −2.00 that was significant on the 5% alpha level resulted. This finding indicated that the effect of the scaffolding self-explanation prompts on procedural knowledge was significantly mediated by the number of incorrect self-explanations. Thus, the scaffolding self-explanation prompts hindered the acquisition of procedural knowledge because they led more frequently to a confusion of principles.

Effects on Subjective Cognitive Load

With respect to research question 5a, we were interested whether the form of representation of the solutions and scaffolding self-explanation prompts influence subjective cognitive load during learning, irrespective of the type of provided representation(s). In a 3 × 2 factorial ANCOVA, we did not obtain a significant main effect of the form of representation, F(2, 112) = 2.28, p = .070, but we found a significant main effect of the scaffolding self-explanation prompts, F(1, 112) = 35.53, MSE = 1.49, p < .001, η² = .24 (see also Table 7). In the groups with scaffolding self-explanation prompts, the participants experienced significantly more subjective cognitive load than their counterparts in the groups without such prompts. This main effect, however, had to be qualified by a significant interaction effect, F(2, 112) = 4.34, p = .015, η² = .08. As you can see in Figure 3, prompts do not seem to heighten subjective cognitive load uniformly in the condition with different representations. We compared the differences between the prompts conditions and the no-prompt conditions when combined with different representations. Learners who received scaffolding self-explanation prompts experienced higher subjective cognitive load when learning with pictorial solutions, F(1, 38) = 10.80, p = .002 (Bonferroni-corrected α = .017; pictorial/self-explanation prompts: M = 3.59, SD = 1.53; pictorial/no self-explanation prompts: M = 3.55, SD = 1.55), or multirepresentational solutions, F(1, 38) = 38.33, p < .001 (Pictorial and arithmetical solutions/No relating aid/Self-explanation prompts: M = 5.10, SD = 1.12; pictorial and arithmetical solutions/no relating aid/no self-explanation prompts: M = 2.90, SD = 1.12;

<table>
<thead>
<tr>
<th>Group</th>
<th>Scaffolding self-explanation prompts</th>
<th>No self-explanation prompts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pictorial solutions</td>
<td>5.15 (1.53)</td>
<td>3.55 (1.55)</td>
</tr>
<tr>
<td>Arithmetical solutions</td>
<td>4.31 (1.13)</td>
<td>3.59 (1.28)</td>
</tr>
<tr>
<td>Multirepresentational (pictorial and arithmetical)</td>
<td>5.10 (1.12)</td>
<td>2.90 (1.12)</td>
</tr>
<tr>
<td>solutions/relating aid</td>
<td>3.99 (1.37)</td>
<td>2.64 (1.21)</td>
</tr>
</tbody>
</table>

Note. The boldface framework represents a 3 (form of representation) × 2 (with vs. without self-explanation prompts) design; the gray shaded condition represents a 2 (with vs. without self-explanation prompts) × 2 (with vs. without a relating aid) design.

Bonferroni-corrected α = .017. We found no significant differences in subjective cognitive load in the case of arithmetical conditions, F(1, 38) = 3.57, p = .067 (arithmetical/self-explanation prompts: M = 4.31, SD = 1.13; arithmetical/no self-explanation prompts: M = 3.59, SD = 1.28).

Furthermore, we were interested, with respect to research question 5b, whether a relating aid and scaffolding self-explanation prompts influence subjective cognitive load during learning with multirepresentational solutions. With respect to the multirepresentational groups of the 2 × 2 design, we found main effects with respect to the relating aid, F(1, 75) = 7.71, MSE = 1.35, p = .007, η² = .09, and with respect to the scaffolding self-explanation prompts, F(1, 75) = 48.24, p < .001, η² = .39. The participants who were provided a relating aid experienced significantly less subjective cognitive load than their counterparts without such a relating aid. In the groups with scaffolding self-explanation prompts, the participants experienced significantly more subjective cognitive load than their counterparts in the groups without such prompts. The interaction between relating aid and scaffolding self-explanation prompts with respect to subjective cognitive load did not reach the level of significance, F(1, 75) = 1.55, p = .218.

In sum, learning without a relating aid increased subjective cognitive load. Scaffolding self-explanation prompts also increased load, except in the case of arithmetical solutions.

Discussion

Against the background of our main findings, we can answer the research questions as follows:

1. The amount of acquired conceptual knowledge did not depend on the type of presented representation(s). It was, however, fostered by scaffolding self-explanation prompts. In addition, when studying multirepresentational solutions, a relating aid further enhanced conceptual knowledge.

2. The procedural knowledge was best fostered by presenting the examples’ solutions merely in arithmetical code. Furthermore, scaffolding self-explanation prompts hin-
dered the acquisition of procedural knowledge when learning with pictorial, arithmetical, or unsupported multi-representational solutions. When learning with multi-representational solutions, the fully supported group, including scaffolding self-explanation prompts and a relating aid, probably prevented such a negative effect on procedural knowledge.

3. The self-explanation activity was influenced by prompts. On the positive side, prompts fostered principle-based self-explanations and rationale-based self-explanations. On the negative side, they also fostered incorrect self-explanations that reflected systematic misunderstandings in terms of the confusion of principles (e.g., confusion of the principles “order relevant” and “order irrelevant,” confusion of the principles “without replacement” and “with replacement,” or confusion of the principles “order” and “replacement”; remember that errors that were not associated with the learning goals of the learning environment were not included in this category).

4. The effects of self-explanation prompts on conceptual knowledge were mediated by the amount of principle-based self-explanations (at least when considering different representational formats) and the amount of rationale-based self-explanations. The negative effect of prompts on procedural knowledge was mediated by incorrect self-explanations in terms of the confusion of principles.

5. Subjective cognitive load during learning was heightened by self-explanation prompts, except in the case of the arithmetical conditions. When providing multiple representations, the subjective cognitive load was reduced by the relating aid.

Against the background of our pattern of results, we can add the following main points to the literature: (a) Our findings suggest that multiple representations do not inherently help to acquire conceptual understanding (i.e., conceptual knowledge). However, we found additive effects of a surface-level help for integration (i.e., relating aid) and a structurally oriented help (i.e., self-explanation prompts). As there were no interaction effects, it was neither the case of one type of help being sufficient nor that a facilitation of relating MERs on the surface level was a prerequisite for structurally oriented integration efforts. Previous research did not analyze the combined effects of surface-level integration support and structurally oriented integration support, except for Seufert and Brünken (2006). In the latter study, however, the authors could not show that their help procedures fostered learning outcomes to a significant degree at all.

(b) We could confirm the conjecture that Roy and Chi (2005) derived from their literature review on self-explanations in multimedia learning environments but did not explicitly test: Self-explanations are suited to foster the integration of MERs and, thereby, foster conceptual understanding. It is, however, important to note that our self-explanation prompts were designed in a way that attention was also directed to integration processes, which differed from the prompts in previous research (e.g., Atkinson, Renkl, & Merrill, 2003; Schworm & Renkl, 2006, 2007); in the latter cases, the prompts typically directed the learners to relate (worked) examples to underlying domain principles.

(c) In contrast to the proposed benefits of learning with multiple representations, for the acquisition of procedural knowledge, it was most helpful to present an arithmetical equation only. This finding suggests that in specific learning situations, it might be sufficient to simply present a single representation.

(d) We showed that scaffolding self-explanation prompts can elicit principle-based and high-quality rationale-based self-explanations. Generating rationale-based self-explanations is extremely demanding for learners without instructional support (see Berthold et al., 2008). Thus, especially with respect to rationale-based self-explanations, it was crucial to provide the learners with scaffolding self-explanation prompts because, without such support, learners rarely generated such self-explanations. Given the aid of the scaffolds in the first isomorphic examples in the conditions with self-explanation prompts, learners were able to perform successfully. Thus, it is expedient to support learners by assistance.
However, the scaffolding self-explanation prompts elicited not only correct self-explanations, but also incorrect self-explanations, which had substantial consequences on the pattern of learning outcomes. Whereas the correct self-explanations fostered conceptual understanding, the incorrect self-explanations hindered the acquisition of procedural knowledge when learning with pictorial, arithmetical, or unsupported multirepresentational representations. The latter finding disconfirms Chi’s (2000) probably too optimistic theoretical account of incorrect self-explanations. Chi (2000) argued that incorrect self-explanations are harmless and may even create an opportunity for cognitive conflicts that eventually lead to further self-explanation episodes and conflict resolution. In some cases, Chi’s (2000) assumptions may be right, for example, when feedback or additional instructional input is given or when the learners commit less severe errors. In our case, the learners mixed up central domain principles when applying them, which hindered the acquisition of procedural knowledge. In such cases, reflection on the misunderstandings and immediate correction, which was not implemented in the present case, might be necessary as instructional support (cf. also Koedinger & Aleven, 2007).

Additionally, our findings show that employing self-explanation prompts belongs to the category of instructional procedures that can show conflicting learning effects (i.e., a positive effect on conceptual knowledge and a negative effect on procedural knowledge when learning with pictorial, arithmetical, or multirepresentational representations). For example, the procedure of interleaving presentation of (related) instructional topics in comparison to block presentation usually slows down learning and immediate performance but leads to better retention or transfer performance (e.g., Richland, Bjork, Finley, & Linn, 2005). Similarly, the variability effect postulated by cognitive load theory (Sweller et al., 1998) suggests that mixed presentation of different problem types (e.g., as worked examples) hinders immediate learning but fosters transfer. Up until now, self-explanation prompts were not regarded as an instructional procedure potentially leading to conflicting learning outcomes. However, our findings show that this can be the case.

With respect to subjective cognitive load, the present findings are in part compatible with cognitive load theory (e.g., Sweller et al., 1998): (a) The relating aid for multiple representations should reduce unproductive visual search processes that induce extraneous load (we actually found that learners’ subjective impressions were of lower load); (b) the prompts should increase learning-related processing that should heighten germane load (we actually found that learners’ subjective impressions were of higher load). However, there are also findings that are not predicted by cognitive load theory. It is unclear why, in the case of arithmetical representations, prompts did not substantially heighten subjective cognitive load and why multiple representations in comparison to single representations did not increase subjective load by their higher complexity (i.e., higher intrinsic load). We informally observed that learners who studied monorepresentational examples—especially in the groups with tree diagrams—often spontaneously translated the representation into another representation (e.g., arithmetical equations). This translation process might have caused increased cognitive load in the monorepresentational groups. Another explanation for the unexpected findings on cognitive load might be that assessing subjective cognitive load is of restricted validity with respect to the actual imposed cognitive load. Hence, in further studies, more objective measures of cognitive load such as dual task measures (e.g., Brünken, Plass, & Leutner, 2003) or pupil dilation (e.g., Van Gerven, Paas, van Merriënboer, & Schmidt, 2004) should be employed.

What implications for instructional design do the present findings have? Four important conclusions can be drawn: (a) Multiple representations per se have little potential to foster conceptual understanding. It is sensible to provide instructional support. (b) When providing multiple representations in order to foster conceptual understanding, it is sensible to enhance integration with surface-oriented instructional aids and, simultaneously, with structurally oriented procedures. One type of integration help is not sufficient. Both support measures seem to have additive effects. (c) Including self-explanation prompts is a sensible measure in order to foster conceptual understanding. (d) Under some conditions, self-explanation prompts may have negative side effects because they elicit wrong explanations. This finding suggests that feedback on the correctness of the provided self-explanation should be provided. Of course, these recommendations have to be considered with caution as long as further studies have not explored the robustness and generalizability of the present findings.

In the following, we discuss a number of possible objections to our findings. A possible critique to the interpretation that conceptual knowledge was actually fostered by helping learners to integrate different representations is that it is not for sure that the participants actually attended to the different representations and that integration processes were necessary in order to gain conceptual understanding. By arguing in favor of the relevance of integrating MERs, we provided theoretical reasons by referring to Ainsworth’s (2006) theoretical framework as well as indirect empirical evidence, such as the significant effect of the relating aid on conceptual knowledge. More direct evidence stems from additional experimental studies that employed the very same worked examples with multirepresentational solutions, including a problem text, a pictorial diagram, and an arithmetical equation as in the present study, and that used eye-tracking technology in order to more directly assess what the learners attended to. Schwonke, Renkl, and Berthold (2007) found that learners inspected all representations and did not simply read the problem text and then look at the arithmetical solution (on average 27% of the total time that the eyes of the participants rested on any of the external representations was spent inspecting the diagram). Although no learner ignored the tree diagrams, the tendency to leave them out from time to time when studying the worked examples (i.e., the number of direct transitions between problem text and arithmetical equation) correlated negatively with the acquisition of conceptual knowledge ($r = -0.46$). Taking up these results, Schwonke, Renkl, and Berthold (in press) instructionally supported (half of) their learners by an informed training. The learners were told to use the tree diagram as a bridge between problem text and equation and to integrate the representations. The informed learners then outperformed their uninformed peers with respect to conceptual knowledge as well transfer performance. Against the background of the present findings and those of Schwonke et al. (2007, in press), it is probable that instructional support measures (e.g., an informed training or a relating aid) are able to support learners to integrate...
MERs and that integrating the representations is crucial for gaining conceptual understanding (i.e., conceptual knowledge). However, a limitation that has to be acknowledged is that in this study no eye-tracking technology was used to assess the eye movements of the learners when studying the multirepresentational solutions. Thus, more research is needed to analyze whether a relating aid and prompts directly lead to more efforts to integrate multiple representations.

Another possible objection with respect to our positive prompt effect on conceptual knowledge will be discussed. By providing only fill-in-the-blank explanations (instead of complete instructional explanations) and by fading out the scaffolds in the isomorphic examples that followed, it was assured that the learners deeply and actively processed the new information by explaining it to themselves. However, as the scaffolding self-explanation prompts included additional information (compared to the open self-explanation prompts), it might be that learning was fostered by the additional information in the scaffolds rather than the scaffolding-fading procedure itself. Hence, it could merely be an effect of receiving an (incomplete) instructional explanation. However, there are two arguments that make this alternative explanation implausible: First, it was found that the quality of self-explanations (i.e., number of rationale-based self-explanations and principle-based self-explanations) mediated the effect of scaffolding self-explanation prompts on conceptual knowledge. Second, there are numerous findings suggesting that usual instructional explanations in worked examples are rather inefficient (e.g., Atkinson & Catrambone, 2000; Atkinson, Catrambone, & Merrill, 2003; Gerjets, Scheiter, & Catrambone, 2003, 2006; Hilbert, Schworm, & Renkl, 2004; Renkl, 2002: Schworm & Renkl, 2006). Thus, it is not probable that the pure reception of the incomplete instructional explanation in the scaffolding self-explanation prompts of the initial worked examples was the crucial factor. Instead, we assume that the supplementary self-explaining in the first example of each pair and the open self-explanation in the second isomorphic example were primarily responsible. To confirm this conjecture, however, researchers should investigate the possible contribution of the additional information in scaffolding self-explanation prompts in future studies.

Another restriction of the present study is that individual differences in working memory capacity were not assessed (e.g., Engle, 2002; Jurden, 1995). This variable determines how easily mental representations can be constructed, how many of them can be held active, and how easily coherence between different information can be established (for an overview, see Feldman Barrett, Tugade, & Engle, 2004). Against this background, individual working memory differences could moderate the effects of the instructional conditions on cognitive load as well as learning outcomes. For example, learners with high working memory capacity might not be overloaded by the demand to process and integrate MERs and, therefore, they might be less dependent on instructional aids in order to gain conceptual understanding. Although cognitive load theory (Sweller et al., 1998), which is one of the main background theories in this study, emphasizes the role of working memory limitations, it has at present hardly stimulated studies in which individual differences in working memory capacities are included. Future studies that consider such individual differences will probably come to a more fine-grained picture on relevant factors contributing to effective learning from MERs.

How far can the present findings be generalized? We have shown the use of two instructional support procedures (relating aid and scaffolding self-explanation prompts) in the context of one domain (i.e., complex events/probability theory). Our research was embedded in mathematics, a well-structured learning domain. As self-explanations in general (i.e., not specifically related to the integration of different representations) have proven to be effective in many domains (e.g., Roy & Chi, 2005), it is probable that the present findings are also valid with respect to scaffolding self-explanations in other multirepresentational learning contents. However, an empirical test of this conjecture requires further inquiry.

A finding that should be replicated in other domains is the additive effect of a surface-level integration support (i.e., relating aid) and a structurally oriented integration support (i.e., self-explanation prompts) with respect to a better conceptual understanding. Not only from a theoretical point of view, but particularly in practical terms, it is important to know whether two types of support procedures are necessary in order to fully utilize the potential of MERs. Finally, it would be interesting to test whether diagnosing the correctness of self-explanations by intelligent tutoring techniques (e.g., Aleven, Popescu, & Koedinger, 2001) and providing corresponding feedback would prevent negative self-explanation prompts effects on procedural knowledge.

References


Schwonke, R., Renkl, A., & Berthold, K. (in press). How multiple external representations are used and how they can be made more useful. *Applied Cognitive Psychology.*


Received February 26, 2007
Revision received April 16, 2008
Accepted May 13, 2008