Instr Sci (2009) 37:345–363
DOI 10.1007/s11251-008-9051-z

Assisting self-explanation prompts are more effective than open prompts when learning with multiple representations

Kirsten Berthold · Tessa H. S. Eysink · Alexander Renkl

Received: 24 November 2006 / Accepted: 19 March 2008 / Published online: 1 April 2008

Abstract Learning with multiple representations is usually employed in order to foster understanding. However, it also imposes high demands on the learners and often does not lead to the expected results, especially because the learners do not integrate the different representations. Thus, it is necessary to support the learners' self-explanation activity, which concerns the integration and understanding of multiple representations. In the present experiment, we employed multi-representational worked-out examples and tested the effects of two types of self-explanation prompts as help procedures for integrating and understanding multiple representations. The participants ($N = 62$) learned about probability theory under three conditions: (a) open self-explanation prompts, (b) self-explanation prompts in an assistance-giving-assistance-withholding procedure (assisting self-explanation prompts), or (c) no prompts (control group). Both types of self-explanation prompts fostered procedural knowledge. This effect was mediated by self-explanations directed to domain principles. Conceptual knowledge was particularly fostered by assisting self-explanation prompts which was mediated by self-explanations on the rationale of a principle. Thus, for enhancing high-quality self-explanations and both procedural knowledge and conceptual understanding, we conclude that assisting self-explanation prompts should be provided. We call this the *assisting self-explanation prompt effect* which refers to the elicitation of high-quality self-explanations and the acquisition of deep understanding.

Keywords Open self-explanation prompts · Assisting self-explanation prompts · Self-explanations · Multiple representations · Mathematics learning

K. Berthold (✉) · A. Renkl
Department of Psychology, Educational and Developmental Psychology, University of Freiburg, Engelbergerstr. 41, 79085 Freiburg, Germany
e-mail: kirsten.berthold@psychologie.uni-freiburg.de

T. H. S. Eysink
Department of Instructional Technology, Faculty of Behavioural Science, University of Twente, 217, 7500 Enschede, The Netherlands

Introduction

Multiple representations (e.g., arithmetical equations and diagrams, cf. Fig. 1) are commonly used in learning materials because they provide unique potentials in fostering understanding. Often, however, multiple representations do not lead to the expected results because the (weaker) learners are overwhelmed and do not integrate the information from different representations (e.g., Moreno and Mayer 1999; Seufert 2003). Recently, Roy and Chi (2005) suggested on the basis of a re-analysis of previous studies that self-explanations are especially suited to foster learning when different representations have to be integrated. This study takes up the assumption of Roy and Chi and analyzes the effects of self-explanation prompts when learning from multiple representations. Furthermore, the effectiveness of different kinds of instructional support for self-explaining are compared (cf. Conati and VanLehn 2000). As learning material, we used worked examples from probability in which we employed multi-representational solutions (for an example of a multi-representational solution, see Fig. 1).

Learning with multiple representations

Why are multiple representations often employed in order to foster understanding? By combining different representations with different properties, learners are not limited by the strengths and weaknesses of one particular representation (cf. Ainsworth 2006; Ainsworth et al. 2002). Furthermore, it is expected that if learners are provided with a rich source of various representations from one domain, they build references across these representations (Ainsworth 2006). In their cognitive flexibility theory, Spiro and Jehng (1990) argue that the ability to construct and switch between multiple representations is

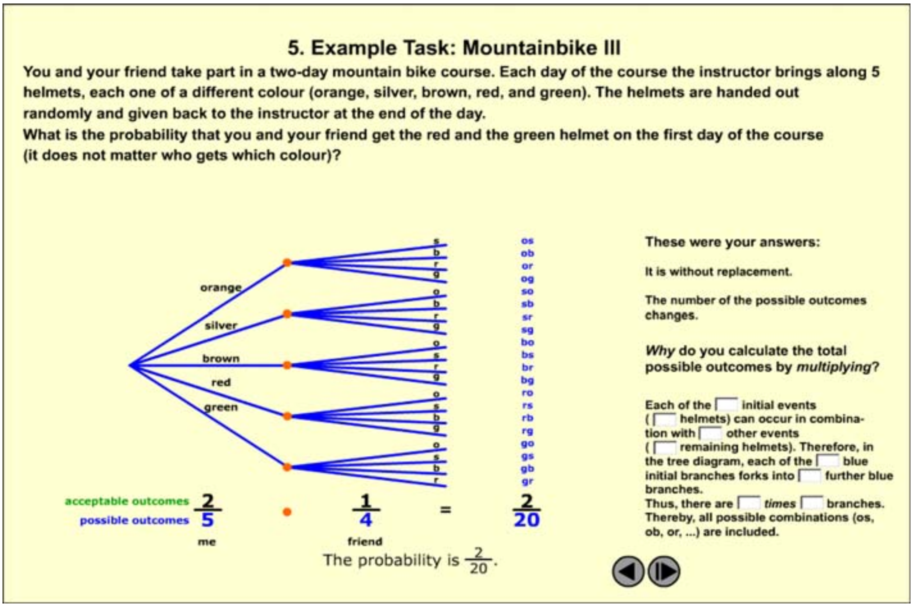

Fig. 1 Screenshot of the learning environment of condition "Assisting self-explanation prompts"

fundamental to successful learning. Mayer (2005) describes a theory of multi-media learning, which states that learners acquire more procedural and conceptual knowledge when they receive multiple representations.

A major problem in employing multiple representations for learning is that often the expected learning outcomes do not occur (e.g., de Jong et al. 1998). Learners experience difficulties particularly when relating the multiple representations to each other. Often they only concentrate on one type of representation or fail to link different representations to each other. As a result, the expected positive effects that were intended by multiple representations do not occur (e.g., Ainsworth et al. 1998). In sum, multiple representations offer unique possibilities of fostering understanding, however, these positive effects often do not occur.

Self-explaining when learning with multiple representations

As already mentioned, Roy and Chi (2005) concluded on the basis of a review on prior studies that self-explanations are especially suited to foster understanding when learning with multiple representations. However, a direct empirical test of the helpfulness of self-explanation for learning with multiple representations is missing.

Self-explanations are explanations that are provided by learners and are mainly directed to themselves (Renkl 2005). They contain information that is not directly given in the learning materials and that refer—in the case of worked examples—to solutions steps and the reasons for them. Many studies have established the benefits of self-explaining with respect to learning processes and learning outcomes specifically in example-based learning (see Chi et al. 1989; Renkl 2005). Meanwhile, a self-explanation effect was also reported for many other learning methods and across many domains, different ranges of age, and learning contexts (Roy and Chi 2005). The role that self-explanation can play in multi-representational understanding has also been considered (cf. Butcher 2006; Roy and Chi 2005). Aleven and Koedinger (2002) argue that self-explanations prove to be particularly beneficial if they help to integrate visual and verbal knowledge. Self-explaining helps these learners to strengthen their verbal declarative knowledge and integrate it with visual knowledge (Ainsworth and Loizou 2003).

However, many learners do not spontaneously engage in effective self-explanation activities (Renkl 1997). This deficit suggests that self-explaining has to be instructionally supported (Renkl 2005).

Prompting self-explanations

Chi et al. (1994) found that spontaneous self-explanations were not as effective as self-explanations that were enhanced by prompting (see also, e.g., Atkinson et al. 2003b; Schworm and Renkl 2007). Prompts are requests that require the learners to process the to-be-learned contents in a specific way (Renkl 2005). They elicit self-explanation activities that the learners are capable of but do not implement unpremeditated (Pressley et al. 1992).

Learners benefit from self-explanation prompts provided by humans (Chi et al. 1994) and by computers (Aleven and Koedinger 2002). Atkinson et al. (2003b) showed that prompting principle-based self-explanations in a computer-based learning environment that provided worked-out examples led to superior learning outcomes in terms of performance on similar problems and novel problems in the domain of probability. Similarly, the study of Aleven and Koedinger revealed that by engaging in self-explanation, learners acquired better-integrated visual and verbal conceptual knowledge and less shallow procedural knowledge. Further evidence for the positive effects of self-explanation prompting when learning from computer-based worked-out examples was provided, for example, by Conati and VanLehn (2000) as well as by Schworm and Renkl (2006, 2007).

However, even if prompted, the use of high-quality self-explanations remains far from optimal, indicating that it is difficult for some learners to engage in this activity (Chi et al. 1989; Renkl 2002; Roy and Chi 2005). Sometimes, learners are not able to self-explain a specific solution step. Furthermore, self-explanations can be fragmented (Roy and Chi 2005). Finally, some learners provide only partially correct or even incorrect self-explanations (Renkl 2002). These deficits in the self-explanations can lead to incomplete or incorrect knowledge that, at worst, can severely impede further learning. Thus, relying only on self-explanations has several disadvantages—even when self-explaining is elicited by prompts.

An own pilot study confirmed these difficulties that the learners had. In this pilot study, we analyzed the effects of open self-explanation prompts (i.e., open questions inducing self-explanations such as, “Why do you calculate the total acceptable outcomes by multiplying?”) with the experimental materials that we used in the present study. It turned out that the learners had severe difficulties in answering the open self-explanation prompts. Oftentimes the learners could not provide the correct explanation. Thus, we assume that some learners profit from stronger instructional support than open self-explanation prompts are able to provide (cf. Roy and Chi 2005).

Assisting self-explanation

Prompts that include some form of instructional assistance (see Koedinger and Aleven 2007) are a promising starting point. Kirschner et al. (2006) and Klahr and Nigam (2004) advocate to provide the learners with more assistance relative to more open approaches (see Anderson et al. 1998). A benefit of giving assistance or information is that learners receive correct information that is communicated efficiently (Koedinger and Aleven 2007). Thereby, errors and floundering (if not complete failure) can be substantially reduced.

According to Vygotskian approaches, providing learners with assistance is related to the zone of proximal development (Vygotsky 1978). This is the region of activity in which learners can perform successfully given the aid of a supporting context. Thus, it is expedient to support learners by assisting on knowledge construction that would be out of reach for the learners without assistance. The intention is, however, to foster subsequent own activity of the learner. The latter implies that after providing learners with assistance, this support is withheld in a subsequent learning phase. Thereby, the learners are encouraged to work on their own.

Yet, previous studies on various assisting procedures in the context of self-explanations provided mixed results. In a qualitative study, Chi (1996) demonstrated that a tutor’s actions of knowledge co-construction—also including self-explanations of the tutees—resulted in tutees’ deep understanding. Hilbert et al. (2004) tried to foster learning either by self-explanation prompts or by a procedure that changed during the course of learning from instructional explanations to self-explanation prompts. The transition from instructional explanations to self-explanation prompts was equally as effective as giving self-explanation prompts alone. Thus, constructing an effective assistance method is not a trivial task. Nevertheless, there are experiments that successfully employed self-explanation prompts that included assisting support in the form of menus providing “building blocks” of self-explanations (Aleven and Koedinger 2002; Conati and VanLehn 2000). Although research has shown that both simple prompting and more elaborate assistance improve self-explanation (Bielaczyc et al. 1995; Chi et al. 1994), no study has yet experimentally compared different kinds of instructional support procedures for self-explaining. However, such a comparison would contribute to an understanding of how much prompting and assisting is necessary to effectively elicit sophisticated self-explanations and thereby foster meaningful learning (cf. Conati and VanLehn 2000).

Overview of the experiment and hypotheses

Against the background of the preceding discussion, it can be argued that supporting self-explanation activity by instructional procedures such as prompting and assisting may bring to bear the advantages of learning with multiple representations. Based on the assumption that assistance supports knowledge construction that would be out of reach for the learners without this assistance, assisting self-explanation prompts may be especially effective with respect to high-quality self-explanations and learning outcomes.

In the present experiment, we investigated the effects of using open self-explanation prompts (open questions that induce self-explanations) and assisting self-explanation prompts (first fill-in-the-blank self-explanations, then open questions) as compared to a no prompt condition. Probability theory was chosen as the learning domain. *Procedural knowledge* and *conceptual knowledge* were assessed as learning outcomes. Procedural knowledge referred to problem-solving performance. Conceptual knowledge referred to knowledge about the rationale of a solution procedure (i.e., why a solution procedure is applied in this way). Specifically, the following hypotheses were tested:

1. Self-explanation prompts (assisting and open) foster high-quality self-explanations of multi-representational examples as compared to no prompts.
2. Assisting self-explanation prompts have additional effects on high-quality self-explanations when compared to open self-explanation prompts.
3. Self-explanation prompts (assisting and open) foster procedural knowledge acquired from multi-representational examples when compared to no prompts.
4. Assisting self-explanation prompts have additional effects on procedural knowledge when compared to open self-explanation prompts.
5. Self-explanation prompts (assisting and open) foster conceptual knowledge acquired from multi-representational examples when compared to no prompts.
6. Assisting self-explanation prompts on multi-representational examples have additional effects on conceptual knowledge when compared to open self-explanation prompts.
7. The (potential) effects on procedural knowledge and conceptual knowledge are mediated by the type of self-explanations.

Furthermore, a focus of our learning environment was on understanding the multiplication rule in probability theory. We were therefore especially interested in factors which enhance the conceptual understanding of the multiplication rule.

Methods

Learning environment and experimental variation

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. In a computer-based learning environment, all learners studied four pairs of isomorphic worked-out examples (i.e., eight examples in total). The worked-out examples demonstrated the application of four principles when determining probabilities in the cases of (a) order relevant, (b) order irrelevant, (c) with replacement, and (d) without replacement. The principles were instantiated by four pairs of isomorphic worked-out examples. In each example pair, the application 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. The participants were allowed to regulate the processing speed of the worked-out examples on their own.

The worked-out examples were presented with multi-representational solution procedures: a pictorial, tree-like solution, and an arithmetical solution (see Fig. 1). The integration of the information from the tree diagram with the respective arithmetical information was supported by an integration aid in form of a combined flashing-color-coding procedure. Corresponding information from the different representations was simultaneously flashing in the same color—"information pair" after "information pair." At the end, a colored freeze image was presented. Thus, corresponding colors cued relations between different representations. This combined flashing and color-coding procedure (Jeung et al. 1997; Kalyuga et al. 1999) was intended to prevent distracting visual search processes (Ayres and Sweller 2005). By supporting the learners in finding the corresponding parts in the different representations, cognitive capacity for self-explanation processes and learning was freed up. An integrated format—usually recommended in the case of two representations—could not be realized because there is no simple one-to-one correspondence between the single elements in the different representations (e.g., in the example depicted in Fig. 1, the "20" in the denominator of the resulting probability corresponds to the 20 branches in the tree diagram; cf. also Renkl 2005).

One focus of our learning environment was 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 multi-representational solution (cf. Fig. 1). The learner can "unpack" it by integrating the information of the multiplication sign of the arithmetical code with the ramifications in the tree-diagram (for the numerator in Fig. 1, there is twice one branch; for the denominator, there are five times four branches).

The experimental variation was realized as follows. Participants of the condition assisting self-explanation prompts received six questions such as "Why do you calculate the total acceptable outcomes by multiplying?" in each worked-out example. In the first worked-out example of each pair of isomorphic examples, the answers were supported in the form of fill-in-the-blank self-explanations [e.g., "There are ___ times ___ branches. Thereby, all possible combinations (os, ob, or, …) are included."]. In the isomorphic examples that followed, this support was withheld, and the participants received six open self-explanation prompts. The answers had to be typed into corresponding text boxes. In the condition open self-explanation prompts, the learners were provided with six open self-explanation prompts only (e.g., open answer to, "Why do you calculate the total acceptable outcomes by multiplying?") in each worked-out example. The assisting self-explanation prompts and the open prompts put an emphasis on relating the pictorial and arithmetical representation to each other. For example, the prompt, "Why is there a four in the denominator of the second single experiment, though there are 20 branches in the tree diagram?" referred to the arithmetical representation ("the four in the denominator") *and*

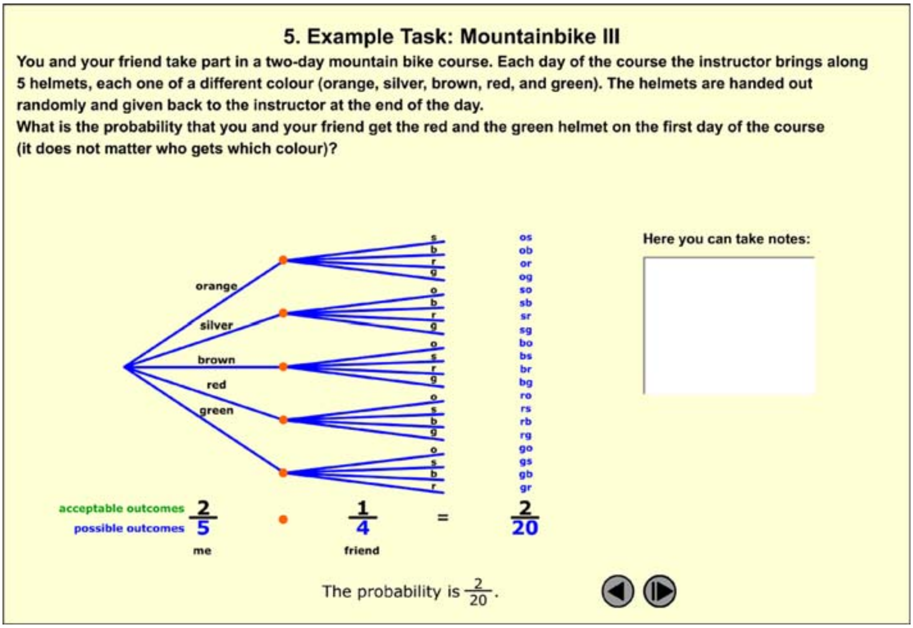

Fig. 2 Screenshot of the learning environment of condition "No self-explanation prompts" (control condition)

to the pictorial representation ("20 branches in the tree diagram"). To answer this question, the learners had to relate the denominator of the arithmetical equation to the corresponding branches of the pictorial tree diagram. Thereby, they could understand that the four stands for the number of remaining events of one initial branch. Due to the fact that there are five initial branches in the first single experiment, five times four branches, that is, 20, are included.

In the condition no self-explanation prompts (control condition), the learners studied the same worked examples as presented in the conditions assisting self-explanation prompts and open self-explanation prompts. The only difference was that the learners of the condition no self-explanation prompts were merely provided with a text box in order to take notes (see Fig. 2) and did not receive any additional support in the form of self-explanation prompts. However, by providing the possibility to take notes, the factors of writing and the possibility to provide explanations in own words were held constant across the three experimental conditions. Thus, a rather strong and thereby fair control condition was implemented.

All prompts and text boxes were placed on the right-hand side of the multi-representational examples. The total size of the text boxes in the self-explanation conditions and the text boxes of the control group for note taking was the same.

Sample and design

The participants of this study were 42 female and 20 male psychology students of the University of Freiburg, Germany. The mean age was approximately 25 years ($M = 25.02$, $SD = 6.12$). The participants were randomly assigned to one of the three conditions of a one-factorial experimental design: "Assisting self-explanation prompts" ($n = 20$), "open self-explanation prompts" ($n = 22$), and "no self-explanation prompts" ($n = 20$). The last condition was the control group.

Procedure

The experiment was conducted in individual sessions. First, the participants were asked to fill out a demographic questionnaire. Afterwards, the learners worked on a pretest. Next, they entered the computer-based learning environment and worked individually in front of a computer. In order to provide or reactivate basic knowledge that allowed the participants to understand the following worked-out examples, an instructional text on the basic principles of probability was provided. Afterwards, the participants studied eight worked-out examples. During this phase, the experimental manipulation was realized, that is, the participants were provided with assisting self-explanation prompts, open self-explanation prompts, or no prompts. Finally, the participants completed a post-test on procedural and conceptual knowledge.

The experiment lasted approximately 2 h ($M = 128.63$ min, $SD = 31.30$). The learning time (i.e., time spent on the worked-out examples) was significantly higher in the groups with self-explanation prompts, $t(60) = 5.65$, $p < .001$ (assisting self-explanation prompts: $M = 73.80$ min., $SD = 20.00$; open self-explanation prompts: $M = 79.41$ min., $SD = 21.62$; no prompts: $M = 46.25$ min., $SD = 17.68$). The two groups with self-explanation prompts did not significantly differ with respect to learning time ($F < 1$). The learning time was not, however, significantly related to the two learning outcome measures: $r = .12$ with procedural knowledge and $r = .17$ with conceptual knowledge. Thus, the variable learning time was not included in further statistical analyses.

Instruments

Pretest: assessment of prior knowledge

A pretest on complex events with six items assessed the topic-specific prior knowledge of the learners. An example pretest item is: "Two coins are tossed. Afterwards, each coin lands heads or tails. What is the probability that one coin lands heads and the other one tails?" The maximum score for the pretest was six points.

Self-explanations: assessment of learning processes

In all groups, the written responses to the prompts were analyzed in detail. As Schworm and Renkl (2006) have shown, the quality of written self-explanations is a good indicator of the quality of the learning processes. The protocols were thoroughly examined for content segments that corresponded to the following high-quality self-explanation categories (Roy and 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 (cf. Renkl 2005). The number of times that participants referred to the principles of the topic complex events 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 the Chi et al.'s (1989) codings of the learners' references to Newton's Laws (the underlying domain principles in that study).

(b) *Rationale-based self-explanations*: this category did not directly correspond to anything in previous studies. It referred to high-quality self-explanations about the rationale of a principle. Thus, rationale-based self-explanations exceed principle-based self-explanations by giving reasons for why the principle is as it is. Hence, for rationale-based self-explanations it was not enough, for example, to state why one has to multiply in the sense of correct application conditions of a principle (e.g., "because it is AND"); the learners also had to state *why* one has to multiply to provide a rationale of the principle itself—typically contextualized in reference to a specific example. A rationale-based self-explanation on the open prompt, "Why do you calculate the total acceptable outcomes by multiplying?" could be: "Because for the denominator there are five *times* four branches. Thus, each of the first five branches of the tree diagram forks out in four further branches because each of the first five events can occur in combination with one of the four remaining events." To provide such a self-explanation it was necessary to integrate the multiplication sign of the equation with the ramifications of the tree diagram. In sum, rationale-based self-explanations in our research typically demanded the integration of two representations and reasoning about why a certain applicable principle has to be applied in a specific way.

The coding categories were distinct. In the assisting self-explanation prompts condition, the learners filled in blanks in the first worked-out example of each pair whereas the learners of the other two conditions answered open self-explanation prompts or just took notes. The statistical analyses in the "Results" section refer only 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; in each condition, the text boxes of every second example were empty.

The written self-explanations of six participants were coded by a student research assistant and the first author. Inter-rater reliability with respect to assigning the protocol segments to the coding categories was very good (Cohen's Kappa .88). In case of divergence, the first author re-examined the protocols and made the final decision. As the inter-rater reliability was very good, the rest of the protocols were only coded by the first author.

Post-test: assessment of learning outcomes

The learning outcomes were measured by a post-test containing 14 problems. These problems were not identical to the pretest problems. Most of these post-test problems were more difficult than the pretest items. Providing these difficult post-test problems in the pretest at the very beginning of the experiment would have probably decreased the self-efficacy of the participants when coping with the demands of the experiment.

Seven post-test problems assessed procedural knowledge, seven problems required conceptual knowledge. The procedural knowledge problems referred to actions or manipulations that are valid within a domain (de Jong and Ferguson-Hessler 1996). This category included transfer items: the surface features and—in some items—the structural features of the problems were changed. An example transfer item is, "Bicycle number-locks usually have four digits. What is the probability that one guesses the right digit sequence on the first guess?" In each task, 0.5 points could be achieved if the numerator of the solution was correct and 0.5 points if the denominator was correct. These scores were summed up to a total score of procedural knowledge. Thus, a maximum score of seven points could be achieved in this category.

Conceptual knowledge problems referred to knowledge about facts, concepts, and principles that apply within a domain (de Jong and Ferguson-Hessler 1996). We focused especially on understanding-why knowledge about the rationale of a solution procedure, that is, why the solution procedures are as they are. Thus, in particular, it includes understanding "what is behind the solution procedure." This category contained seven open questions which required written explanations of conceptual knowledge of principles presented in the learning phase. For example, the learners were to explain *why* the multiplication rule has to be applied (e.g., "Why are the two fractions multiplied?"). As the rationale for the multiplication rule can be figured out relatively easily when the pictorial and the arithmetical representations are integrated, this post-test measure also assessed the quality of representation integration. Two independent raters, who were blind to experimental conditions, scored the open answers by using a 6-point rating scale ranging from 1 (*no conceptual understanding*) to 6 (*very clear conceptual understanding*). A very clear conceptual understanding was indicated by a correct answer with a high degree of reasoning and elaboration. Inter-rater reliability was very good (intra-class coefficient .90). In cases of divergence, the final coding was determined by discussion.

Results

Table 1 presents the means and standard deviations for the three experimental groups on the pre-test, on principle-based self-explanations and rationale-based self-explanations, as well as on procedural and conceptual knowledge. Additionally, scores on the understanding of the multiplication rule (which was part of the conceptual knowledge) is reported.

The measures on learning outcomes were subjected to a priori contrasts that corresponded to the hypotheses (i.e., one-tailed t-tests). According to the recommendations of Rosenthal and Rosnow (1985) (see also Rosenthal et al. (2000), we refrained from reporting overall ANOVA results (except for the students' topic-specific prior knowledge). Of particular interest were contrasts comparing the (aggregated) self-explanation groups with the no-prompts group (control group) and contrasts comparing the assisting self-explanation group with the open self-explanation group. The latter accounted for additional

Table 1 Means and standard deviations (in parentheses) on the pre-test, on the self-explanation measures, and on the learning outcome measures

	Pre-test	Principle-based explanations	Rationale-based explanations	Procedural knowledge	Conceptual knowledge	Multiplication rule
No prompts	2.35 (1.86)	1.47 (2.80)	.05 (.23)	3.63 (1.36)	2.58 (.77)	1.85 (.89)
Open self-explanation prompts	2.52 (1.69)	6.55 (2.76)	2.50 (3.39)	4.41 (1.05)	2.98 (.87)	2.00 (1.08)
Assisting self-explanation prompts	2.30 (1.41)	7.75 (2.38)	11.20 (7.57)	4.55 (1.20)	3.63 (1.02)	3.57 (1.65)

effects of the assisting self-explanation group when compared with the open self-explanation group. An alpha-level of .05 was used for all statistical analyses. As an effect size measure, we used *d*—qualifying values of approximately .20 as weak effect, values of approximately .50 as medium effect, and values of approximately .80 or bigger as large effect (cf. Cohen 1988).

With respect to the students' topic-specific prior knowledge, an ANOVA revealed no significant differences, $F < 1$. Hence, there was no a priori difference between groups with respect to this important learning prerequisite.

Effects of self-explanation prompts on self-explanations

Descriptively, higher means for principle-based self-explanations emerged in the groups with self-explanation prompts (assisting self-explanation prompts and open self-explanation prompts). As mentioned above, we aggregated the two groups with self-explanation prompts and compared them with the no-prompts group (control group) in order to test this difference. A *t*-test yielded a significant and very strong difference for principle-based self-explanations in favor of the self-explanation prompts groups, $t(59) = 7.63$, $p < .001$, $d = 2.08$ (due to technical problems, a process data set of one participant in the group with no prompts was lost; thus, the degrees of freedom are reduced by one in the corresponding analyses). Hence, the self-explanation prompts elicited significantly more principle-based self-explanations when compared with the no-prompts group. A *t*-test on potential additional effects of assisting self-explanation prompts on principle-based self-explanations when compared to open self-explanation prompts failed to reach statistical significance, $t(40) = 1.51$, $p = .070$. Thus, the two groups with self-explanation prompts did not significantly differ in their amount of principle-based self-explanations. In sum, assisting and open self-explanation prompts fostered principle-based self-explanations. Yet, the two self-explanation prompts groups did not differ in this respect.

With respect to rationale-based self-explanations, we obtained descriptively higher means in the groups with self-explanation prompts (assisting self-explanation prompts and open self-explanation prompts). A *t*-test revealed a significant and strong difference for rationale-based self-explanations in favor of the (aggregated) self-explanation prompts groups, $t(41) = 5.93$, $p < .001$, $d = 1.29$ (*t*-test for unequal variances). A *t*-test on additional effects of assisting self-explanation prompts on rationale-based self-explanations yielded a significant and strong effect in favor of the assisting self-explanation prompts, $t(26) = 4.73$, $p < .001$, $d = 1.48$ (*t*-test for unequal variances) when compared to open self-explanation prompts. Thus, assisting self-explanation prompts had additional effects on rationale-based self-explanations in comparison to open self-explanation prompts. In summary, with respect to rationale-based self-explanations, assisting and open self-explanation prompts were effective. Assisting self-explanation prompts in particular elicited these types of self-explanations.

Effects of self-explanation prompts on learning outcomes

As Table 1 shows, we obtained higher means for procedural knowledge in the groups with self-explanation prompts (assisting self-explanation prompts and open self-explanation prompts). To test this difference, the (aggregated) groups with self-explanation prompts were compared to the control group. A *t*-test yielded a significant and medium to strong difference for procedural knowledge in favor of the self-explanation prompts groups, $t(60) = 2.62$, $p = .005$, $d = .68$. Hence, the participants who had received self-explanation prompts performed significantly better on procedural knowledge than those learners who had received no such prompts.

A *t*-test on additional effects of assisting self-explanation prompts on procedural knowledge, when compared to open self-explanation prompts, failed to reach statistical significance, $t(40) = .41$, $p = .688$. Thus, the two groups with self-explanation prompts did not differ with respect to procedural knowledge. In summary, with respect to procedural knowledge, assisting and open self-explanation prompts fostered procedural knowledge. The two self-explanation prompts groups did not differ in this respect.

With respect to conceptual knowledge, the descriptively highest mean was obtained in the assisting self-explanation prompts group, followed by the mean of the open self-explanation prompts group. The lowest mean was revealed for the no-prompts group (cf. Table 1). A *t*-test comparing the groups with self-explanation prompts against the no-prompts group (control group) yielded a significant and strong effect, $t(60) = 2.84$, $p = .003$, $d = .80$. The participants of the self-explanation prompts groups outperformed their counterparts in the no-prompts groups with respect to conceptual knowledge. A *t*-test contrasting the assisting self-explanation prompts group with the open self-explanation prompts group revealed a significant and medium to strong effect, $t(40) = 2.23$, $p = .016$, $d = .68$, in favor of the first group. Thus, assisting self-explanation prompts had additional effects on conceptual knowledge in comparison to open self-explanation prompts.

A special focus of our learning environment was on understanding *why* the multiplication rule has to be applied. This type of knowledge also indicates to what extent the different representations were integrated because it can hardly be understood by studying just one representation. We tested whether assisting and open self-explanation prompts fostered understanding of the multiplication rule. Descriptively, we obtained the highest mean in the assisting self-explanation prompts group, whereas the means of the open self-explanation prompts and no-prompts group were relatively low (cf. Table 1). A *t*-test, which tested whether the groups with self-explanation prompts outperformed the no-prompts group, revealed a significant and medium to strong effect, $t(58) = 2.85$, $p = .003$, $d = .70$ (*t*-test for unequal variances). Hence, the participants of the groups with self-explanation prompts outperformed their counterparts of the no-prompts group with respect to understanding the multiplication rule. A *t*-test on the question of whether assisting self-explanation prompts fostered understanding of the multiplication rule more effectively than open self-explanation prompts yielded a significant and strong effect, $t(32) = 3.60$, $p = .001$, $d = 1.13$ (*t*-test for unequal variances). Correspondingly, the overall pattern of performance indicated that, above all, assisting self-explanation prompts fostered the integration of multiple representations.

In summary, self-explanation prompts on multi-representational examples fostered principle-based self-explanations and rationale-based self-explanations as well as procedural and conceptual knowledge. With respect to principle-based self-explanations and to procedural knowledge, it did not make a difference whether the learners were provided with assisting or with open self-explanation prompts. However, with respect to rationale-based self-explanations and conceptual knowledge (especially, understanding of the multiplication rule), the overall effect of the self-explanation prompts can be ascribed mainly to the assisting self-explanation group.

Mediation of the learning outcomes by self-explanations

Having established that the prompts conditions fostered principle-based self-explanations *and* procedural knowledge compared to the no-prompts condition, the question arises whether the principle-based self-explanations mediated the effects on procedural knowledge. Furthermore, the assisting prompts version in particular elicited rationale-based self-explanations *and* fostered conceptual knowledge. This finding suggests that conceptual knowledge was fostered *via* rationale-based self-explanations. Against this background, we addressed the following questions: Can the effects on procedural knowledge be explained by an increase of principle-based self-explanations? Can the effects on conceptual knowledge be explained by an increase of rationale-based self-explanations? To answer these questions, we conducted two mediation analyses.

To test whether principle-based self-explanations do indeed *mediate* the influence of the independent variable *prompts* (self-explanation prompts versus no prompts) on procedural knowledge, 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, (1) the independent variable (i.e., prompts) must affect the dependent variable (i.e., procedural knowledge), (2) the independent variable (i.e., prompts) must affect the potential mediator (i.e., principle-based self-explanations), and (3) 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 10% of the variance in the scores of procedural knowledge (9% adjusted), $F(1, 61) = 6.86$, $p = .011$. The second analysis demonstrated the influence of the independent variable prompts on principle-based self-explanations, $F(1, 60) = 58.13$, $p < .001$; it accounted for 50% of the variance in the principle-based self-explanations. In the third regression analysis, procedural knowledge was regressed on the factor prompts and principle-based self-explanations in a simultaneous multiple regression model. This regression equation accounted for 17% of the variance (14% adjusted), $F(2, 60) = 5.74$, $p = .005$. As expected, principle-based self-explanations significantly predicted procedural knowledge, ß = .38, $t(60) = 2.24$, $p = .029$, whereas the influence of the factor prompts was no longer significant, ß = −.04, $t(60) = -.23$, $p = .823$. Following Baron and Kenny (1986) and MacKinnon (2002), this pattern of results indicates mediation. In order to directly test whether the mediation effect differed significantly from zero, we used the test procedure suggested by MacKinnon (2002) (see also MacKinnon and Dwyer 1993). This test procedure included the computation of two regression equations: Mediator = a*Independent + error_1 and Dependent = c*Independent + b*Mediator + error_2. 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 $a{*}b$, $se_{ab} = \sqrt{(a^2{*}[se_b]^2 + b^2{*}[se_a]^2)}$ (cf. Sobel 1982). In such an analysis, we obtained a z score of −2.14 that was significant on the 5% level. This finding indicated that the effect of the prompts on procedural knowledge was significantly mediated by the number of principle-based self-explanations. Thus, the prompts fostered procedural knowledge because the self-explanation prompts effectively supported the learners in generating principle-based self-explanations.

Furthermore, we tested whether rationale-based self-explanations mediated the influence of the independent variable *assisting prompts versus open prompts* on conceptual knowledge. Therefore, three further regression equations were estimated and tested for significance. The first analysis demonstrated that the type of prompts (assisting prompts versus open prompts) accounted for 11% of the variance in conceptual knowledge (9% adjusted), $F(1, 41) = 4.96$, $p = .032$. A second analysis showed that the independent variable (assisting prompts versus open prompts) significantly influenced the potential mediator (i.e., rationale-based self-explanations). This regression equation accounted for 37% of the variance (36% adjusted), $F(1, 41) = 23.84$, $p < .001$. Thirdly, the influence of the independent variable (assisting prompts versus open 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. This regression equation accounted for 28% of the variance (24% adjusted), $F(2, 41) = 7.44$, $p = .002$. As expected, rationale-based self-explanations significantly predicted conceptual knowledge, ß $= .52$, $t(60) = 2.99$, $p = .005$, whereas the influence of the factor assisting prompts versus open prompts was no longer significant, ß $= -.02$, $t(60) = -.103$, $p = .919$. In a mediation analysis according to MacKinnon (2002), we obtained a z score of -2.53 that was significant on the 1% level. Thus, the rationale-based self-explanations did in fact mediate the impact of the assisting prompts on conceptual knowledge. Conclusively, the assisting prompts fostered conceptual knowledge because the assisting prompts effectively supported the learners in generating rationale-based self-explanations.

Discussion

In summary, our study made five essential contributions to the problem of supporting effective self-explanations during learning with multi-representational examples: (a) Self-explanation prompts (assisting and open) foster principle-based self-explanations and rationale-based self-explanations. With respect to rationale-based self-explanations, assisting self-explanation prompts are especially effective. (b) Self-explanation prompts foster procedural and conceptual knowledge in multi-representational learning. (c) With respect to fostering principle-based self-explanations and procedural knowledge, it is equally effective to use open or assisting self-explanation prompts. Principle-based self-explanations are the crucial mediator in fostering procedural knowledge. (d) With respect to fostering rationale-based self-explanations and conceptual knowledge, assisting self-explanation prompts are especially effective. Thereby, we were able to show that assisting self-explanation prompts have an additional value when compared to open prompts (cf. Conati and VanLehn 2000). Rationale-based self-explanations mediated the effects on conceptual knowledge. (e) Assisting self-explanations are particularly effective for integrating multiple representations, as indicated by the understanding of the multiplication rule. This rule can be understood by integrating the multiplication sign of the arithmetical equations and the ramifications of the tree diagram. Thus, our findings also suggest that assisting self-explanation prompts particularly support the integration of multiple representations.

The present findings confirm the assumption of Roy and Chi (2005) as well as Aleven and Koedinger (2002) that self-explanations are suited for integrating multiple representations and, thereby, fostering learning outcomes. In comparison to other integration aid procedures, such as the use of an integrated format, the employment of self-explanation prompts has the advantage that it goes beyond the surface level with respect to the integration of different representations. They require the learner to focus on the *conceptual* correspondences (cf. Seufert and Brünken 2004), such as the type of correspondence between the multiplication sign in the arithmetical equation and the ramification in the tree diagram in the present learning environment.

Against the background of the additional effect of assisting self-explanation prompts, the following question arises: Why were assisting self-explanation prompts in particular powerful with respect to fostering rationale-based self-explanations and thereby enhancing conceptual knowledge, whereas with respect to principle-based self-explanations and procedural knowledge, providing open self-explanation prompts were sufficient? Conceptual understanding (e.g., understanding the multiplication rule) is more demanding than gaining procedural knowledge—in particular because such a type of conceptual understanding is seldom addressed in mathematics lessons in school or at university. Nevertheless, it is crucial for further learning. The finding that assisting self-explanation prompts (as opposed to open self-explanation prompts) were shown to be effective with respect to the elicitation of the highly demanding rationale-based self-explanations, the integration of multiple representations, and conceptual knowledge supports the assumptions of Koedinger and Aleven (2007). The authors suggests that a rough criterion for deciding to give rather than withhold assistance is when the task gets too difficult (i.e., highly demanding self-explanations and conceptual knowledge) and thus the probability of failure or unproductive thinking is too high. Similarly, the findings may be related to the zone of proximal development (Vygotsky 1978). Generating the highly demanding self-explanations and acquiring the demanding conceptual knowledge was slightly out of reach for learners without the assisting self-explanation prompts. For instance, most of the learners were not able to self-explain the rationale of the multiplication rule—even if they were prompted by open self-explanation prompts. Open prompts were only capable of eliciting self-explanations that the learners were capable of but did not spontaneously generate—such as the principle-based self-explanations. In contrast, the highly demanding rationale-based self-explanations could only be elicited if, in the initial worked-out examples, the fill-in-the-blank self-explanations provided the learners with the pieces of information that they needed to integrate and to conceptually understand the multi-representational examples (e.g., "There are ___ times ___ branches. Thereby, all possible combinations are included."). Conceptual understanding refers in particular to a deep understanding of the rationale of (multi-representational) solution procedures. Evidently, the assistance supported the learners in the troublesome process of understanding the background of the multi-representational solutions. As a consequence, our findings suggest that assisting self-explanation prompts should be provided if understanding the learning contents is slightly out of reach for learners without assistance. We call this the *assisting self-explanation prompt effect*, which refers to the elicitation of high-quality self-explanations and the acquisition of deep understanding.

However, diagnosing the dimensions of the zone of proximal development is a difficult task (Ainsworth et al. 1998). We should nevertheless be able to identify its lower boundary by analyzing the learner's unsupported performance. With this information, it should be possible to construct assisting prompts on knowledge that is out of reach for the unsupported learner and which therefore falls within the learner's zone of proximal development. In future studies, learning environments with multiple representations could be designed that include different types of assisting self-explanation prompts for learners at different levels of skill acquisition (cf. Conati and VanLehn 2000). Furthermore, self-explanations could be diagnosed online in order to provide an immediate and dynamic adaptation of assisting procedures (e.g., Aleven et al. 2001).

By including only fill-in-the-blank self-explanations instead of complete instructional explanations in the assisting self-explanation prompts and by withholding this assistance in the following isomorphic examples, it was assured that the learners did not just superficially and passively, but rather actively processed the new information by explaining it to themselves. Nevertheless, there are two restrictions with respect to our interpretation of the effects of the assisting self-explanation prompts. (a) The first restriction is that possibly not the assistance-giving-assistance-withholding procedure on the whole (first isomorphic examples: fill-in-the-blank explanations; second isomorphic examples: open self-explanation prompts) is crucial with respect to fostering the acquisition of procedural and conceptual knowledge but only the part of the fill-in-the-blank explanations in the first isomorphic examples. Future studies should additionally compare the effects of an assistance-giving-assistance-withholding procedure versus fill-in-the-blank explanations only to come to a more fine-grained picture about the relevant parts of the assistance-giving-assistance-withholding procedure. Thereby, it would be possible to analyze if the reduction in support in the assistance-giving-assistance-withholding procedure would indeed be helpful. (b) The second restriction also refers to the fill-in-the-blank explanations in the first isomorphic examples. Thereby, the assisting self-explanation prompts included additional information compared to the open self-explanation prompts. Thus, it might be that not filling in the blanks and answering the subsequent open self-explanation prompts was helpful but only the *additional information* in the assisting prompts fostered learning. Hence, it could be merely 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) mediated the effect of assisting self-explanation prompts on conceptual knowledge. Secondly, there have been numerous findings in the mean time, which show that usual instructional explanations in worked-out examples are rather inefficient (e.g., Atkinson and Catrambone 2000; Atkinson et al. 2003a; Gerjets et al. 2003; Hilbert et al. 2004; Renkl 2002). Thus, it is not probable that the pure "reception" of the incomplete instructional explanation in the assisting self-explanation prompts in the initial worked-out examples was the crucial factor. Instead, we assume that the supplementary self-explaining in the first example of each pair and the open self-explanations in the second isomorphic example were crucial. This interpretation is supported by Siegler (2002) who asked learners to self-explain either their own or another's answers (i.e., the experimenter's answers). The latter is similar to our assistance in the learning environment because both Siegler's and our learners had to self-explain (part of) an expert's answer. Participants who were best in explaining the presented answers of the experimenter also showed the best results in providing correct answers on their own. Evidently, self-explaining a pre-existing answer of an expert more effectively fostered understanding than explaining one's own answer. This was probably also due to the fact that the pre-existing answers were consistently correct whereas the answers of the participants without this scaffold were fragmented or (partially) incorrect. When explaining a provided correct answer, additional opportunities arise for comparing and contrasting this answer with one's own (cf. Roy and Chi 2005). Observing discrepancies between a correct answer and one's own will naturally elicit repairs of one's own representation and thereby foster learning (Chi 2000). Nevertheless, these learning processes only occur if the learners actively self-explain a presented answer or, in our case, the information included in the assisting self-explanation prompts in some form (e.g., by filling in blanks and answering open self-explanation prompts). Thus, self-explaining is probably the crucial factor. However, an empirical test of the specific contribution of the additional information in assisting self-explanation prompts is necessary in future studies.

A further question that is raised refers to the generalizability of the present results. We have shown the use of (assisting) self-explanation prompts for the integration of multiple representations in the context of mathematics, a well-structured learning domain. As self-explanation in general (i.e., not specifically related to the integration of different representations) has proven to be fruitful in many domains (e.g., Roy and Chi 2005), we conjecture that it is appropriate to generalize the present findings across different learning contents. Nevertheless, an empirical test of this conjecture is necessary in future studies.

In a nutshell, the findings suggest the following instructional implication for learning with multiple representations. Assisting self-explanation prompts can strongly foster the integration and understanding of multiple representations: they elicit high-quality self-explanations that are slightly out of reach for learners without this assistance and foster deep conceptual understanding (assisting self-explanation prompt effect). The case of the assisting self-explanation prompt effect is a very good instance to support the notion that effective learning needs a well-balanced mixture of provided assistance and information (e.g., assisting self-explanation prompts) and room for active knowledge construction (e.g., self-explanations) (cf. Renkl 2005).

However, constructing assisting self-explanation prompts is rather time-consuming and demanding for the instructor. Thus, we plea for the implementation of assisting self-explanation prompts only if understanding the learning contents is out of reach for the learners without this instructional support measure (i.e., conceptual knowledge). In this case, the development of the sophisticated assistance procedure is worth the effort because the additional effects justify the costs of construction. Otherwise (i.e., fostering procedural knowledge), it might be sufficient to provide open prompts which are less costly to construct. Thus, against the background of the learning goal (i.e., conceptual versus procedural knowledge), the instructor has to decide how much prompting and assistance is necessary to effectively elicit self-explanations and enhance learning outcomes (cf. Conati and VanLehn 2000).

Acknowledgments The research reported in this article was funded by the "Deutsche Forschungsgemeinschaft" (DFG 1040/11-1). We would like to thank the members of the Dutch-German LEMMA cooperation project (project leaders: Peter Gerjets, Ton de Jong, Jeroen van Merriënboer, and Fred Paas) for jointly constructing the tasks of the learning environment as well as Julian Kappich, Norman Marko, Heidi Roeder, Tim Rohe, and Stephan Rueckert for their assistance in programming, conducting the experiment, coding the self-explanations, and analyzing the tests.

References

Ainsworth, S. E. (2006). DeFT: A conceptual framework for considering learning with multiple representations. *Learning and Instruction, 16*, 183–198.

Ainsworth, S. E., Bibby, P. A., & Wood, D. J. (1998). Analysing the costs and benefits of multi-representational learning environments. In H. Spada, P. Reimann, E. Boshuizen, & T. de Jong (Eds.), *Learning with multiple representations* (pp. 120–134). Oxford: Elsevier Science.

Ainsworth, S. E., Bibby, P. A., & Wood, D. J. (2002). Examining the effects of different multiple representational systems in learning primary mathematics. *The Journal of the Learning Sciences, 11*, 25–61.

Ainsworth, S. E., & Loizou, A. (2003). The effects of self-explaining when learning with text or diagrams. *Cognitive Science, 27*, 669–681.

Aleven, V., & Koedinger, K. R. (2002). An effective metacognitive strategy: learning by doing and explaining with a computer-based Cognitive Tutor. *Cognitive Science, 26*, 147–179.

Aleven, V., Popescu, O., & Koedinger, K. R. (2001). Towards tutorial dialog to support self-explanation: Adding natural language understanding to a cognitive tutor. In J. D. Moore, C. L. Redfield, & W. L. Johnson (Eds.), *Artificial intelligence in education: AI-ED in the wired and wireless Future, Proceedings of AI-ED 2001* (pp. 246–255). Amsterdam: IOS Press.

Anderson, J. R., Reder, L. M., & Simon, H. A. (1998). Radical constructivism and cognitive psychology. In D. Ravitch (Ed.), *Brooking papers on education policy 1998* (pp. 227–278). Washington, DC: Brookings Institute Press.

Atkinson, R. K., & Catrambone, R. (2000). Subgoal learning and the effect of conceptual vs. computational equations on transfer. In L. R. Gleitman & A. K. Joshi (Eds.), *Proceedings of the 22nd Annual Conference of the Cognitive Science Society* (pp. 591–596). Mahwah, NJ: Erlbaum.

Atkinson, R. K., Catrambone, R., & Merrill, M. M. (2003a). Aiding transfer in statistics. Examining the use of conceptually oriented equations and elaborations during subgoal learning. *Journal of Educational Psychology, 95*, 762–773.

Atkinson, R. K., Renkl, A., & Merrill, M. M. (2003b). Transitioning from studying examples to solving problems: Combining fading with prompting fosters learning. *Journal of Educational Psychology, 95*, 774–783.

Ayres, P., & Sweller, J. (2005). The split-attention principle in multimedia learning. In R. E. Mayer (Ed.), *Cambridge handbook of multimedia learning* (pp. 135–146). Cambridge, UK: Cambridge University Press.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*, 1173–1182.

Bielaczyc, K., Pirolli, P., & Brown, A. L. (1995). Training in self-explanation and self-regulation strategies: Investigating the effects of knowledge acquisition activities on problem-solving. *Cognition and Instruction, 13*, 221–252.

Butcher, K. R. (2006). Learning from text with diagrams: Promoting mental model development and inference generation. *Journal of Educational Psychology, 98*, 182–197.

Chi, M. T. H. (1996). Constructing self-explanations and scaffolded explanations in tutoring. *Applied Cognitive Psychology, 10*, 33–49.

Chi, M. T. H. (2000). Self-explaining expository texts: The dual processes of generating inferences and repairing mental models. In R. Glaser (Ed.), *Advances in instructional psychology* (pp. 161–238). Mahwah, NJ: Lawrence Erlbaum Associates.

Chi, M. T. H., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science, 13*, 145–182.

Chi, M. T. H., de Leeuw, N., Chiu, M. H., & Lavancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive Science, 18*, 439–477.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Conati, C., & VanLehn, K. (2000). Toward computer-based support of meta-cognitive skills: A computational framework to coach self-explanation. *International Journal of Artificial Intelligence in Education, 11*, 398–415.

de Jong, T., Ainsworth, S., Dobson, M., van der Hulst, A., Levonen, J., Reimann, P., Sime, J.-A., van Someren, M. W., Spada, H., & Swaak, J. (1998). Acquiring knowledge in science, mathematics: The use of multiple representations in technology-based learning environments. In M. van Someren, P. Reimann, H. P. A. Boshuizen, & T. de Jong (Eds.), *Learning with multiple representations* (pp. 9–40). Amsterdam: Pergamon.

de Jong, T., & Ferguson-Hessler, M. G. M. (1996). Types and qualities of knowledge. *Educational Psychologist, 31*, 105–113.

Gerjets, P., Scheiter, K., & Catrambone, R. (2003). Reducing cognitive load and fostering cognitive skill acquisition: Benefits of category-avoiding examples. In F. Schmalhofer, R. Young, & G. Katz (Eds.), *Proceedings of the European Cognitive Science Conference* (pp. 133–139). Mahwah, NJ: Erlbaum.

Hilbert, T. S., Schworm, S., & Renkl, A. (2004). Learning from worked-out examples: The transition from instructional explanations to self-explanation prompts. In P. Gerjets, J. Elen, R. Joiner, & P. Kirschner (Eds.), *Instructional design for effective and enjoyable computer-supported learning* (pp. 184–192). Tübingen: Knowledge Media Research Center.

Jeung, H., Chandler, P., & Sweller, J. (1997). The role of visual indicators in dual sensory mode instruction. *Educational Psychology, 17*, 329–343.

Kalyuga, S., Chandler, P., & Sweller, J. (1999). Managing split-attention and redundancy in multimedia instruction. *Applied Cognitive Psychology, 13*, 351–371.

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experimental, and inquiry-based teaching. *Educational Psychologist, 42*(2), 75–86.

Klahr, D., & Nigam, M. (2004). The equivalence of learning paths in early science instruction: Effects of direct instruction and discovery learning. *Psychological Science, 15*, 661–667.

Koedinger, K. R., & Aleven V. (2007). Exploring the assistance dilemma in experiments with Cognitive Tutors. *Educational Psychology Review, 19*(3), 239–264.

MacKinnon, D. P. (2002). Mediating variable. In N. J. Smelser & P. B. Baltes (Eds.), *International encyclopaedia of the social and behavioral sciences* (pp. 9503–9507). New York: Elsevier.

MacKinnon, D. P., & Dwyer, J. H. (1993). Estimating mediated effects in prevention studies. *Evaluation Review, 17*, 144–158.

Mayer, R. E. (2005). Cognitive theory of multimedia learning. In R. E. Mayer (Ed.), *Cambridge handbook of multimedia learning* (pp. 31–48). Cambridge, UK: Cambridge University Press.
Moreno, R., & Mayer, R. E. (1999). Multimedia-supported metaphors for meaning making in mathematics. *Cognition and Instruction, 17*, 215–248.
Pressley, M., Wood, E., Woloshyn, V. E., Martin, V., King, A., & Menke, D. (1992). Encouraging mindful use of prior knowledge: Attempting to construct explanatory answers facilitates learning. *Educational Psychologist, 27*, 91–109.
Renkl, A. (1997). Learning from worked-out examples: A study on individual differences. *Cognitive Science, 21*, 1–29.
Renkl, A. (2002). Learning from worked-out examples: Instructional explanations support self-explanations. *Learning and Instruction, 12*, 529–556.
Renkl, A. (2005). The worked-out example principle in multimedia learning. In R. E. Mayer (Ed.), *Cambridge handbook of multimedia learning* (pp. 229–247). Cambridge, UK: Cambridge University Press.
Rosenthal, R., & Rosnow, R. L. (1985). *Contrast analysis: Focused comparisons in the analysis of variance*. Cambridge, UK: Cambridge University Press.
Rosenthal, R., Rosnow, R. L., & Rubin, D. B. (2000). *Contrast and effect sizes in behavioural research. A correlational approach*. Cambridge, UK: Cambridge University Press.
Roy, M., & Chi, M. T. H. (2005). The self-explanation principle in multi-media learning. In R. E. Mayer (Ed.), *Cambridge handbook of multimedia learning* (pp. 271–287). Cambridge, UK: Cambridge University Press.
Schworm, S., & Renkl, A. (2006). Computer-supported example-based learning: When instructional explanations reduce self-explanations. *Computers and Education, 46*, 426–445.
Schworm, S., & Renkl, A. (2007). Learning argumentation skills through the use of prompts for self-explaining examples. *Journal of Educational Psychology, 99*, 285–296.
Seufert, T. (2003). Supporting coherence formation in learning from multiple representations. *Learning and Instruction, 13*, 227–237.
Seufert, T., & Brünken, R. (2004). Supporting coherence formation in multimedia learning. In P. Gerjets, J. Elen, R. Joiner, & P. Kirschner (Eds.), *Instructional design for effective and enjoyable computer-supported learning* (pp. 138–147). Tübingen: Knowledge Media Research Center.
Siegler, R. S. (2002). Microgenetic studies of self-explanation. In N. Granott & J. Parziale (Eds.), *Microdevelopment: Transition processes in development and learning* (pp. 31–58). New York: Cambridge University Press.
Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. In S. Leinhardt (Ed), *Sociological methodology* (pp. 290–312). Washington, DC: American Sociological Association.
Spiro, R. J., & Jehng, J.-C. (1990). Cognitive flexibility and hypertext: Theory and technology for nonlinear and multi-dimensional traversal of complex subject matter. In D. Nix & R. J. Spiro (Eds.), *Cognition, education, and multi-media: Exploring ideas in high technology*. Hillsdale, NJ: LEA.
Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (M. Cole, V. John-Steiner, S. Scribner, & E. Souberman, Eds. and Trans.). Cambridge, MA: Harvard University Press.