LEARNING FROM WORKED-OUT EXAMPLES:

MULTIPLE REPRESENTATIONS, AN INTEGRATION HELP, AND SELF-EXPLANATION PROMPTS ALL FOSTER UNDERSTANDING

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OVERVIEW

Multiple representations (e.g., an equation and a diagram) are commonly used because they can provide unique benefits when learners are trying to gain a deep understanding (Ainsworth, in press). Regrettably, many studies have shown that this promise is not always achieved. Often, learners are overwhelmed with the complex demands of integrating and understanding multiple representations. This suggests that learners might profit from learning with multiple representations to a larger extent when instructional support measures on integrating and understanding are employed.

Therefore, the main goal of this dissertation is to experimentally investigate the effects of multiple representations and two corresponding instructional support measures on learning processes (i.e., *self-explanations*) and learning outcomes (i.e., *conceptual* and *procedural knowledge*). Do students learn more deeply from multiple representations than from one representation alone? Do instructional support measures such as an integration help in form of flashing and color-coding as well as self-explanation prompts further enhance the benefits of multiple representations? What are the crucial processes with this respect? These questions are the focus of this dissertation.

To address these questions, two experiments were conducted in which we employed worked-out examples from the domain of probability theory and tested the effects of multiple representations, an integration help in form of a flashing-color-coding procedure, and self-explanation prompts. In *Experiment 1*, the effects of two types of self-explanation prompts (scaffolding vs. open) as help procedures for integrating and understanding multiple representations were analyzed. *Experiment 2* additionally tested the effects of multi- vs. mono-representational solutions and an integration help. The findings of Experiment 1 were taken up insofar in Experiment 2 as we implemented scaffolding self-explanation prompts which proved to be effective in Experiment 1.

Overall, results showed that multiple representations embedded in worked-out examples and an integration help fostered conceptual knowledge. With respect to procedural knowledge, it was equally effective to provide multi- or mono-representational solutions or presenting the multi-representational solutions with or without an integration help. Self-explanation prompts fostered high-quality self-explanations and conceptual knowledge. With respect to conceptual knowledge, scaffolding self-explanation prompts were especially effective when compared to open prompts (*scaffolding self-explanation effect*). Though, scaffolding self-explanation prompts also evoked incorrect self-explanations that impaired the acquisition of procedural knowledge (*paradox self-explanation prompt effect*).

Chapter 1 provides the general theoretical background for this dissertation involving a disambiguation as well as information about the learning approach and the domain of this research. In chapter 2, the computer-based learning environment which was developed for this research is described. Chapter 3 provides an overview of the two experiments of this dissertation and the main research questions are elaborated. In chapter 4 and 5, the two experiments are presented that examined the effects of multiple representations, an integration help, and self-explanation prompts. These chapters include a theoretical introduction addressing the specific research problem, a presentation of the corresponding research questions, the method and results as well as a discussion of the findings. Chapter 4 on Experiment 1 describes the effects of two types of self-explanation prompts as help procedures for integrating and understanding multiple representations. Chapter 5 on Experiment 2 presents the effects of multi- vs. mono-representational solutions, an integration help in form of a flashing-color-coding procedure, and scaffolding self-explanation prompts. Chapter 6 concludes with an overall discussion of the findings, theoretical and practical implications, limitations as well as an outline of future research directions.

1. General Theoretical Background

The following chapter provides the general theoretical background for this dissertation. First, the topic of multimedia learning is addressed because learning from multiple representations is often discussed under this heading. The second section introduces the learning approach multi-representational worked-out examples and corresponding theories. The third section deals with learning mathematics by multiple representations.

1.1 Multimedia Learning

In this section, first, a disambiguation of the term *multimedia learning* is aimed. Afterwards the question “How can multimedia (not) foster meaningful learning?” is discussed.

1.1.1 A Disambiguation

New technologies in general and multimedia in particular play an increasingly important role in learning and teaching (Schnotz & Lowe, 2003). When reading the term *multimedia*, you might think of a computer with an integrated video, oral explanations, as well as texts, pictures, and maybe other forms of information such as arithmetical equations. Although the term multimedia is widespread, it is not suitable in its everyday sense for the scientific discourse (cf. Weidenmann, 1997). Against this background, some experts in the field (Mayer, 2005b; Schnotz, 2005; Weidenmann) propose to differentiate different meanings of the term multimedia. According to Weidenmann, the term multimedia confounds the categories medium, modality, external, and internal representation. Hence, instead of using the undifferentiated, sweeping catchword of multimedia, he suggests to distinguish between the following categories:

(a) Medium. Mediums are objects or technical devices which can communicate or construct messages, for example, a personal computer or a book (Weidenmann, 1997). Similarly, Mayer (2005b) and Schnotz (2005) refer to this category as technical level. Thus, the term *multimedium-based* includes at least two mediums which are presented in an integrated manner, for example, a personal computer including a video (Weidenmann). The medium is of course very important in practice. Yet, from an educational point of view comprehension is not fundamentally different when a text passage is delivered either by a computer screen or a printed book (cf. Schnotz). Similarly, Clark (1994) made the explicit and clear claim that there were no pure learning benefits possible due to mediums. Already in his early articles, Clark (cf. 1983, 1985) claimed, in part, that media are "mere vehicles that deliver instruction but do not influence student achievement any more than the truck that delivers our groceries cause changes in our nutrition" (1983, p. 445). Meta-analytic reviews of media research which have produced evidence for the positive learning benefits of research with various media were confounded because of not controlling the instructional method. Consequently, Clark (e.g., 1983) argues that it is the method which influences learning, not the medium. Further, any necessary teaching method could be designed into a variety of media presentations. Clark (1994) defines methods as the provision of cognitive processes or strategies that are necessary for learning but which students cannot or will not provide for themselves.

(b) Modality (Schnotz, 2005; Weidenmann, 1997). The term modality refers to the sense which is addressed (visual, auditive). If only one sense is addressed, Weidenmann uses the term "mono-modal" (e.g., only visual or only auditive). The term "multi-modal" is appropriate, if different senses receipt signs, for example, the eyes and ears are addressed

which can be realized by an audio-visually presentation (e.g., written text and oral text) (cf. sensory level; Mayer, 2005b).

(c) External representation (cf. Ainsworth, in press) or codality (codes or symbol systems; cf. Weidenmann, 1997). The learning content can be presented in different formats and symbol systems, that is, different external representations (e.g., verbal, pictorial, arithmetical). Multiple external representations include the use of different forms of representations (cf. Schnotz, 2005), for example, a pictorial tree diagram and an arithmetical equation. Some authors (e.g., Ainsworth, in press) refer to external representations as *modality*. Instead, in this dissertation, it is proposed to use the term *codality* when referring to representational systems (e.g., arithmetical equations). Modality, in contrast, should be used when referring to senses (e.g., visual or auditive) (see last paragraph).

(d) Internal representation (mental representation or mental format, cf. Weidenmann, 1997). If the learners actively process the external representations, the learning content is mentally encoded. Thus, the learners build internal representations. It has to be stressed that there is no one-to-one correspondence between the external and the internal representation (cf. Weidenmann). When learners understand texts and pictures, they construct multiple mental representations (cf. Schnotz, 2005). A textual input (external representation) might also be visually encoded (internal representation), and a picture (external representation) can lead to mental propositional (textual) representations (cf. Zimmer, 1993). In a nutshell, the external representation is not inevitably identical with the internal representation.

1.1.2 How Can Multimedia Presentation (Not) Foster Meaningful Learning?

A number of misconceptions arise amongst educators because of a failure to distinguish these different levels (cf. Weidenmann, 1997). In fact, previous research on so-called “media-effects” has clearly established that it is misguided and overly simplistic to compare different technical media with regard to their effects on learning without taking into account the aspects of modality, external, and internal representations. As mentioned above, Clark (1983, 1985) presented evidence in support of the hypothesis that instructional methods had been confounded with media and that it is methods which influence learning. Clark (1994) suggests that our failure to separate medium from method has caused enormous confounding and waste in a very important and expensive research area.

Rather, the other levels (modality, external, and internal representations) are generally the crucial factors and a proper understanding of them requires expertise in cognitive science, psychology, and educational science (Mayer, 2005b). Thus, rather than searching for technical media-effects, research on learning and instruction should focus on the levels of modality and external representations as well as on their effect on internal representations that constitute comprehension and learning (Mayer, 2005b; Schnotz, 2005).

Unfortunately, there are also misconceptions with respect to the level of modality and external representations (Mayer, 2005b), for example, that rich learning environments with powerful visualization and sound techniques result in extensive cognitive processing and thus create elaborated knowledge structures (cf. Schnotz, 2005). Consequently, the learners are often completely overwhelmed. Therefore, recently a stronger focus is put on more specific questions, for example, how learning environments including multiple representations foster meaningful learning. Against this background, this dissertation focuses exclusively on learning with multiple representations (external representations) – thereby only addressing the visual sense (modality).

Multiple representations in learning materials (e.g., text and pictures) are commonly used because they provide unique potentials in fostering understanding. Unfortunately, many studies have shown that the promise of multiple representations is not always achieved (cf. Ainsworth, in press). Evidently, multiple representations – and especially their integration – impose high demands on the cognitive processing of the learners including the danger of overwhelming the learners. What could be a sensible solution?

1.2 The Learning Approach: Multi-Representational Worked-Out Examples

An important step towards the solution of the problem that multiple representations can overwhelm the learners may be to use a learning approach and learning materials which reduce demands on the learner. One such effective and “load-saving” method is learning from worked-out examples. Worked-out examples consist of a problem formulation, solution steps, and the final solution itself. When it is referred to the term *learning from worked-out examples* or *example-based learning* (both terms are used as synonyms) in this research, it is always meant that more than just a single example is used because it is more effective to use a series of worked-out examples (cf. Sweller & Cooper, 1985).

Research has shown that learning from such examples is of major importance for the initial skill acquisition of cognitive skills and learning in well-structured domains such as mathematics, physics, and programming (for an overview see VanLehn, 1996). Often learners have a limited understanding of the domain when they try to solve the first problems and would be completely overwhelmed with complex, demanding learning arrangements. Typically, learners rely on general, domain unspecific problem-solving heuristics such as means-ends analysis (Renkl, 2005). Thereby, they might even find the right solution. However, such striving for the correct answer does not lead to a profound understanding of the domain. The basic idea of example-based learning is to reduce problem solving demands by providing worked-out solutions in initial stages of skill acquisition, when gaining understanding is the instructional main goal (cf. Sweller, van Merriënboer, & Paas, 1998). Thereby, more of the learners’ limited processing capacities (i.e., working memory capacities) can be devoted to understanding the domain principles and their application in problem solving (Renkl, 2005). These assumptions are summarized in the worked-out principle in learning that states that learners gain a deep understanding of a skill domain when they receive worked-out examples in the beginning of cognitive skill acquisition. In this case, learners can also engage in domain-specific reasoning, which in turn can deepen their understanding. However, many learners do not use their available processing capacities for trying to self-explain the example solutions to themselves (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Renkl, 1997). Accordingly, they gain little understanding. Prompts (requests directed to learners; cf. Renkl, 2005) for self-explaining example solutions have been shown to successfully prevent this problem and foster learning outcomes (e.g., Atkinson, Renkl, & Merrill, 2003; Berthold, Nückles, & Renkl, 2006).

Against the background that (a) worked-out examples leave relatively many cognitive resources for gaining understanding and (b) multiple representations and especially their integration require many cognitive resources, it is sensible to combine multiple representations and worked-out examples by embedding multi-representational solutions in worked-out examples. In this dissertation such examples are called multi-representational examples.

The use of examples – in contrast to problems to-be-solved – leaves more processing capacities so that there is a better chance that learners can successfully cope with the high demands of learning from multiple representations. There are mainly two types of theoretical approaches that are relevant when analyzing learning with multi-representational examples.

Theories on learning from multiple representations. The most intriguing aspect of learning with multiple representations is that understanding occurs when learners are able to build meaningful connections between multiple representations – such as being able to see how an arithmetical equation is related to a diagram. In the process of trying to build connections between two or more representations, learners are able to create a deeper understanding than from one representation alone. This idea is at the heart of the theories of learning with multiple representations (cf. Mayer, 2005b).

Ainsworth (1999, in press; Ainsworth, Bibby, & Wood, 1998) intends to formulate guidelines for when (and when not) to employ multiple representations. As many studies have shown, multiple representations are not always useful (e.g., de Jong et al., 1998; Hegarty, Narayanan, & Freitas, 2002; Schnotz, Böckheler, Grzondziel, Gärtner, & Wächter, 1998). Learners often do not map different representations onto each other so that the positive effects that were intended by the use of multiple representations do not occur to the expected extent (e.g., Ainsworth et al., 1998; Tabachnek-Schijf & Simon, 1998). Hence, multi-representational learning environments have to be carefully designed. Crucial aspects in this context are the specific functions of multiple representations and the task that learners have when processing these multiple representations (cf. Ainsworth, in press). With this respect, guidance has to be provided for how to process the presented information – that is, for determining what to pay attention to, how to mentally organize it, and how to relate it to prior knowledge (Mayer, 2005b).

Theories with a capacity focus. Both the cognitive load theory (Sweller, 1999, 2005; Sweller et al., 1998) and the theory of multimedia learning (Mayer, 2005a; Mayer & Moreno, 2003) emphasize processing structures and limitations. A potential problem of learning from multiple representations is that the learners are overwhelmed by the complexity of the presented learning materials and the corresponding processing demands. Instructional prescriptions are formulated that try (a) to minimize unproductive processes in working memory that are not related to the relevant aspects of the learning contents (e.g., “unnecessary” visual search processes) and (b) to maximize cognitive processes that are related to understanding and learning outcomes. These instructional prescriptions also apply on worked-out examples with multi-representational solutions. In order to profit from the potential of multiple representations, it is in most cases necessary to understand the relation between different representations. Based on cognitive load theory, two ways of fostering the integration of different representations and understanding can be distinguished:

(a) Reducing cognitive load that is not related to processes of learning (reduction of extrinsic load). It is aimed to avoid, for example, visual search processes that do not contribute to understanding and take away attention from processing the relevant learning contents. A typical recommendation derived from cognitive load theory is to integrate two information sources (e.g., pictorial tree diagram and arithmetical equation) into one information source by bringing corresponding elements spatially close to each other (principle of *integrated format*; cf. Ayres & Sweller, 2005). Across several experiments, Sweller and his colleagues documented that non-integrated material hindered learning, presumably because the learners had to retain the equations in their working memory as they attempted to locate the relevant elements in the diagram (Sweller, Chandler, Tierney, & Cooper, 1990; Tarmizi & Sweller, 1988). On the other hand, they found that an integrated format facilitated learning. The option of spatial integration, is, however, not always possible, for example, when elements in one representation do not correspond to certain, well-circumscribed parts in the other representation (e.g., one number of the arithmetical equation corresponds to several branches of a tree diagram). In this case, other support measures can be used such as color-coding (i.e., assigning the same color to corresponding elements) or flashing (i.e., corresponding elements flash simultaneously) (cf. Jeung, Chandler, & Sweller, 1997; Kalyuga, Chandler, & Sweller, 1999). For instance, incorporating flashing in computer-based learning environments can successfully guide learners as they attempt to make sense of the presented material (Jeung et al.). This is particularly true for situations with high visual-search complexity. Essentially, using signals to help learners discriminate relevant from irrelevant information can help them effectively integrate multiple representations.

(b) Increasing learning related processing (increasing germane load). To benefit from the advantages of multiple representations, one challenge is to engage learners in the active knowledge construction necessary for learning (Roy & Chi, 2005) which requires considerable cognitive capacity. Yet, making salient which elements correspond does not

ensure that the conceptual relations between the representations are in fact detected. A potential problem is that learners' mapping may remain at the surface level (cf. Seufert & Brünken, 2004). In order to foster conceptual mapping, the learners should actively integrate multiple representations (cf. Bodemer, Plötzner, Feuerlein, & Spada, 2004). A promising approach are self-explanation prompts that direct the learners' self-explanations on integrating and understanding multiple representations. Self-explanations are explanations that are provided by learners and mainly directed to themselves (Renkl, 2005). People learn more deeply when they spontaneously engage in or are prompted to provide explanations during learning (Roy & Chi). Self-explanations contain information that is not directly given in the learning materials and that refer to solution steps and the reasons for them. Several key cognitive mechanisms are involved including generating inferences to fill in missing information, integrating information within the study materials, referring to structural and surface features of problems or problem types, integrating new information with prior knowledge, and monitoring and repairing faulty knowledge. Thus, self-explaining on multi-representational examples is a cognitively demanding but deeply constructive activity (Roy & Chi) and is contextualized in a specific domain (i.e., mathematics).

1.3 Learning Mathematics by Multiple Representations

Clearly, multi-representational learning is applicable across a wide range of domains (Atkinson, 2005). In multi-representational learning on science, a considerable amount of research has been conducted (for a review, see Mayer & Moreno, 2002). Though, the experimental research focusing on issues related to multi-representational learning of mathematics is relatively small in comparison. While the educational literature is filled with many examples of articles describing "best practices" or explorative studies, there is an extremely modest amount of sound, empirically based research (Atkinson, 2005).

Consequently, more experimental research is needed to explore how to advance learners' understanding and learning in mathematics using multi-representational learning environments. However, in a recent review article focusing on learning with animations (Mayer & Moreno, 2002), out of the 31 experiments cited as the sources, only one experiment involved mathematics.

Beyond the deficit of research on learning mathematics by multiple representations, there is a lack of addressing *different* mathematical topics. In the available research geometry instruction is focussed (for an exception see Große & Renkl, in press).

Indeed, geometry is an ideal mathematical subdomain to explore the effectiveness of learning with multiple representations given that words and graphics are so prevalent during instruction. However, it is critical that the empirically derived instructional principles devoted from these geometrical learning materials be generalized to additional mathematical subdomains. Therefore, it is important to examine whether these findings can be generalized beyond geometry instruction to other subdomains of mathematics.

Beyond the underrepresentation of mathematics in sound research on multiple representations, interpretation of the nature of mathematical understanding has changed recently. The focus has shifted from the learning of formal procedures and accepted facts to an emphasis on mathematics as flexible, insightful understanding (Ainsworth, 1997). Similarly, the National Council of Teachers of Mathematics' 1989 launched the present debate for the de-emphasis of rote practice and rote memorization of rules and algorithms (Schoenfeld, 2004). Consistent with this approach, educational researchers such as Robert Davis (1986) state:

> If "mathematics" is seen as conformity to memorized rituals, if it is taught without meaning...if meaningfulness compels a slow pace and a vast investment in repetition, and if routine calculation is the main goal, very little mathematics will be included in the curriculum (pp. 272–273).

Both aspects – (a) the deficit of experimental research in mathematical topics others than geometry and (b) the emphasis on mathematics as insightful understanding – are addressed in this research. With respect to (a), the mathematical subdomain that is chosen in this research is probability theory. This topic is an important part of mathematical competence (cf. the mathematical area *uncertainty* in PISA; Blum et al., 2004). More specifically, the topic of complex events in probability theory was chosen. Beyond the argumentation of Atkinson (2005), this is a subdomain that is suited for the use of different representation codes (i.e., pictorial and arithmetical), that generally has a relatively high difficulty level for learners, and that is an important part of school curricula. With respect to (b), the learning environment and tests address an insightful understanding of mathematical rationales.

2. Learning Environment

In this section, the learning environment which was conceptually constructed and programmed (in Authorware 7.0) by the author is described. Probability theory (specifically: complex events) was chosen as the learning domain (cf. previous section). The computer-based learning environment included eight worked-out examples in which mono-representational or multi-representational solution procedures (pictorial, tree-like solution and an arithmetical solution; cf. Figure 1) were embedded.

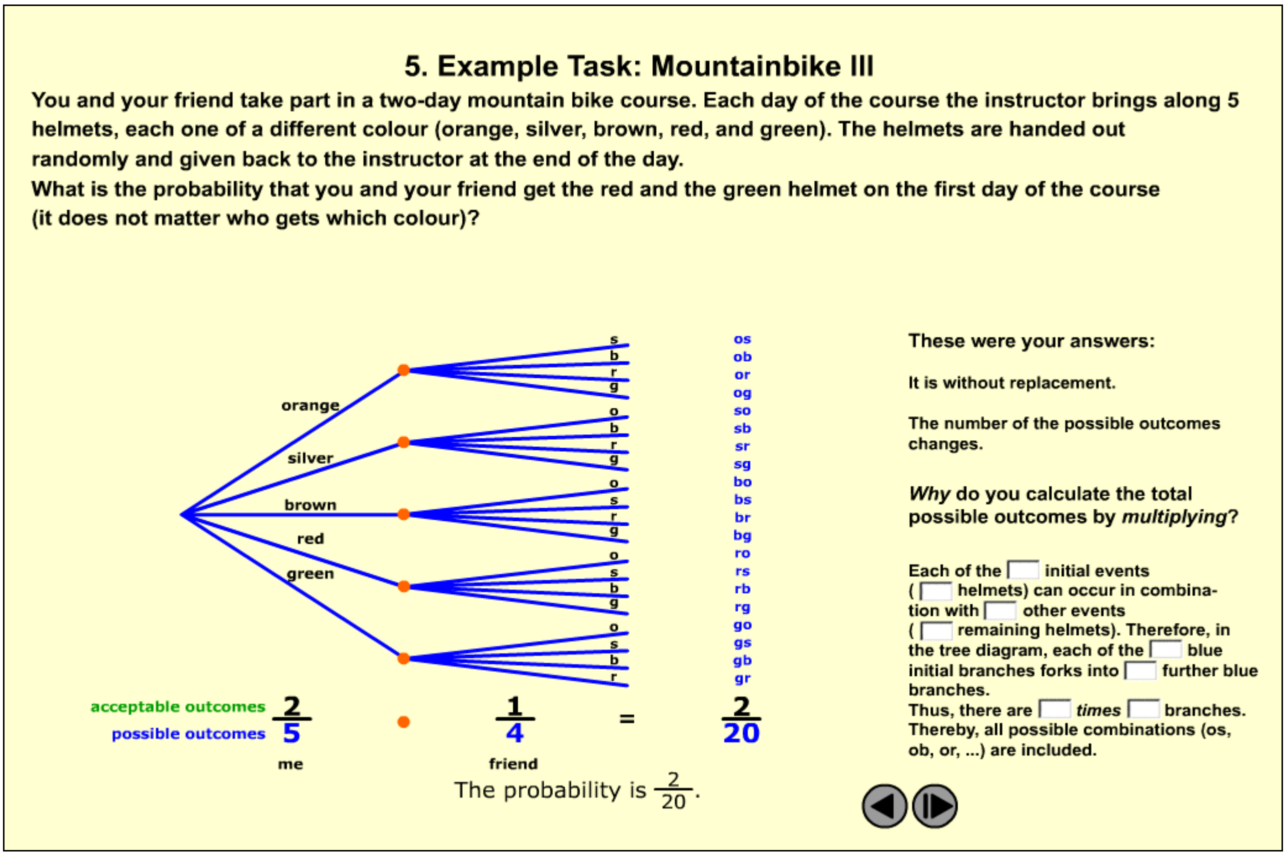

Figure 1

Screenshot of the Learning Environment

The cover stories of the tasks included realistic considerations (e.g., Cooper & Harries, 2003). The participants regulated the processing speed of the worked-out examples on their own.

Specifically, in the worked-out examples four principles were addressed that are to be applied 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.

One special 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. Figure 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 Figure 1, there is twice one branch; for the denominator, there are five times four branches).

The worked-out solution procedures were *modular* (i.e., composed of a number of separate units) – in contrast to *molar* procedures including a "holistic" formula (Gerjets, Scheiter, & Catrambone, 2004). In other words, the probabilities of the *single* selections were determined and multiplied (cf. Renkl, 2005). In Figure 1, the multi-representational worked-out solution procedure includes a modular solution. Particularly when integrating the information of the modular equation with the tree-like diagram, the learners can figure out with relative ease why this solution works (e.g., a 4 in the denominator of the second single event can be mapped on the four branches of the second ramification of the tree diagram).

Contrary, in statistics and mathematics text books as well as in school lessons, molar solution procedures are frequently used that are computationally efficient but hard to understand. For example, the problem displayed in Figure 1 could have been solved in a molar way by the general formula 1/(n!/[n-k]! k!), where *n* is the number of possible events and *k* is the number of selections. Gerjets et al. (2004) compared molar and modular worked-out solution procedures from probability in several experiments. The computationally not so efficient modular solution procedures led to better performance on isomorphic as well as novel problems. The modular solutions are called *conceptually oriented equations* by Atkinson, Catrambone, and Merrill (2003), and these authors also obtained positive effects on transfer tasks.

In the learning environment of this dissertation, the learners should especially learn how the multiplication rule is applied in problem solving (procedural knowledge) and about the rationale of the multiplication rule (conceptual knowledge about the "why" of solutions). Thus, beyond employing conceptually oriented (modular) equations, it was decided to direct the attention of the learners on the numerator and the denominator separately by a combined color and flashing procedure (see below). Thereby, the learners tried to understand the multiplication rule on a combinatorics level. In this vein the understanding of the multiplication rule was facilitated. This was due to the fact that when integrating the information of the multiplication sign of the equation with the ramifications of the tree diagram, the learner can immediately see that for the numerator, there is twice one branch and for the denominator, there are five times four branches. Thus, for example, for the denominator each of the five first branches of the tree diagram forks out in four further branches because each of the first five events can occur in combination of one of the four remaining events. The prerequisite for this understanding is to separately process the numerator and denominator as well as the modular presentation of the equation. If the equation was presented in a molar way (i.e., 1/(n!/[n-k]! k!), the learners would have had little chance to detect the combinations of the single events, that is, understanding the rationale of the multiplication rule.

In addition, in Experiment 1 and in two of the multi-representational conditions in Experiment 2, the learners were supported in integrating the arithmetical information (e.g., the multiplication signs) and the information from the tree diagram (e.g., the ramifications) by an integration help: Corresponding information from the different representations were 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) should prevent a high level of *extraneous load* (load not directly relevant to learning) due to a type of split-attention effect (Ayres & Sweller, 2005). By supporting the learners in finding the corresponding parts in the different representations, cognitive capacity for self-explanation processes and learning was released. An integrated format – as 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 Figure 1, the “20” in the denominator of the resulting probability corresponds to the twenty branches in the tree diagram; cf. also Renkl, 2005).

Furthermore, some experimental conditions included scaffolding self-explanation prompts (“fill-in-the-blank” explanations) or open self-explanation prompts (open questions). This experimental manipulation is described in more detail in section 4.5.1 and in section 5.5.1).

In the following, the learning environment is classified according to Ainsworth’s DeFT-framework (Ainsworth, in press). Specifically, it is characterized in more detail with respect to the criteria of design, functions, and learners' cognitive tasks. This description refers to the version of the learning environment that is theoretically the best for the specified learning goals (Figure 1). In the experiments described later, some features (e.g., self-explanation prompts) are omitted in order to test the theoretical rationale and the effects of these features.

Design. In our learning environment, the solution part contains three co-present representational codes (pictorial, arithmetical, and textual scaffolds included in self-explanation prompts). Some important information is distributed over the arithmetical, pictorial, and textual representation (e.g., the rationale of the multiplication rule). The arithmetical representation (see Figure 1) includes the information that the fractions have to be multiplied – a fact that most learners grasp rather easily. However, most learners do not understand why the fractions have to be multiplied. This information is encapsulated in the tree diagram (e.g., for the denominator, there are five times four branches). Nevertheless, this information is often not apparent to the learners. Detecting this information is scaffolded by the self-explanation prompts including textual information (see Figure 1, the text with blanks beside the tree diagram). These scaffolding self-explanation prompts include some to-be-supplemented instructional text in the first example of a problem type. In the second example of a problem type, an open self-explanation prompt is provided that just includes a question (e.g., "Why is the total number of possible events determined by multiplication?").

The translation (Ainsworth, in press) between the multiple representations was facilitated at the representation and the domain level (cf. Seufert & Brünken, 2004). At a representation level, the learners are supported in integrating the arithmetical information (e.g., the multiplication signs) and the information from the tree (e.g., the ramifications) by an integration help (see above). At a domain level, the learners were supported to relate the multiple representations to each other and to the domain by scaffolding self-explanation prompts (e.g., “There are ... times ... branches. Thus, all possible outcomes are included.”). As the interpretation of representations is an inherently contextualised activity, it is crucial to identify the relations between the representation and the domain it represents. This task is particularly difficult for learners because this understanding must be forged upon incomplete domain knowledge. Thus, corresponding scaffolding is sensible (cf. section 4.3).

The learning environment included mostly static multi-representational systems. Only the integration help was dynamic. The multi-representational solutions (tree-like solutions and arithmetical equations) were flashing at the same time. After the flashing procedure, scaffolding self-explanation prompts appeared.

Functions. Multiple representations serve at least three different instructional functions in supporting learning: to complement, to constrain, and to construct (Ainsworth, in press). The multiple representations of this learning environment had some *complementary functions* – multiple representations complement each other by supporting different complementary processes or containing complementary information. For example, the information of the multiplication sign in the arithmetical code showed *that* one has to multiply, whereas the ramifications of the tree-diagram showed *why* one has to multiply. Furthermore, representations differ in their advantages for learning specific knowledge. Thus, the task that is to be accomplished by the learners after learning is the crucial factor to decide which representation(s) are the best. Performance following learning is most likely to be facilitated when the structure of information required by the task matches the form provided by the representational notation (Ainsworth, in press; Brünken, Steinbacher, Schnotz, & Leutner, 2001; Schnotz, 2005). Thus, the function of a representation is directly related to the learning goals to be achieved.

With respect to constraining functions – two representations constrain and thereby support each other's interpretation – one can state that the ramifications in the pictorial tree-diagram constrained the meaning of the multiplication sign in the arithmetical equations – indicating that the multiplication represents the combination of different events.

Finally, the multiple representations in our learning environment supported the construction of deeper understanding when learners integrate information from the different representations to achieve insight that would be difficult to gain by studying only a single representation (*constructing functions*). Thus, the three representations (arithmetical, pictorial, and textual) were designed to foster deep-level conceptual knowledge with a focus on understanding the rationale of solutions. The learners were supposed to abstract over representations to identify the shared invariant features of the domain.

The differences between these functions of multiple representations are subtle (cf. Ainsworth, in press). The multiple representations included in the learning environment of this research incorporated to some extent all three functions.

Learners' cognitive tasks. The cognitive tasks that a learner must perform to learn from multiple representations include understanding the properties of the representations and the relation between the representations and the domain. The cognitive demand unique to multiple representations is to understand how to translate between two representations. There is much evidence that this translation / integration is difficult for learners.

The learning environment of this dissertation contained representations of different *codalities.* These representations are known to have very different computational properties (e.g., Larkin & Simon, 1987). Consequently, learners may find it difficult to see the relationship between such different forms of representation. In the learning environment, the learners had to understand how to translate the problem formulation into a pictorial tree-diagram and an arithmetical equation as well as relate the multi-representational solution to the domain. As already mentioned, the learners were supported by self-explanation prompts in the corresponding conditions. In addition, the integration of representations was supported by an integration help including flashing and color-coding (Jeung et al., 1997; Kalyuga et al., 1999).

It is important to have a detailed characterization of the learning environments because it is not sensible to assume that multi-representational learning environments and included support procedures have per se certain effects on learning (Ainsworth, in press). Factors such as the ones discussed above have to be considered when predicting effects and when comparing effects in different studies on learning with multiple representations.

3. Overview of the Experiments and Research Questions

The main goal of this dissertation is to experimentally study the effects of multiple representations and two instructional support measures on learning processes and learning outcomes. Do students learn more deeply from multiple representations than from one representation alone? Do instructional support measures such as an integration help in form of flashing and color-coding as well as self-explanation prompts further enhance the benefits of multiple representations? What are the crucial processes with this respect? These questions are the focus of this dissertation.

As explicated before (cf. section 1.2), it can be argued that the employment of well-designed worked-out examples reduces extraneous cognitive load which enables the learners to use “free” cognitive capacity with respect to the integration and understanding of multiple representations. This in turn may bring to bear the advantages of learning with multiple representations, at least when the self-explanation activity is supported by instructional procedures such as prompting and scaffolding.

To test these assumptions, a computer-based learning environment (cf. section 2) including eight worked-out examples was developed. In the experiments described later, some features (e.g., self-explanation prompts) were omitted in order to test the theoretical rationale and the effects of these features.

In this dissertation, two experiments will be presented that examined the effects of multiple representations, an integration help, and self-explanation prompts. In Experiment 1 (cf. chapter 4) the effects of two types of self-explanation prompts (scaffolding vs. open) as help procedures for integrating and understanding multiple representations were analyzed. Experiment 2 (cf. chapter 5) tested the effects of multi- vs. mono-representational solutions and an integration help. Furthermore, the findings of Experiment 1 with respect to effective self-explanation prompts were taken up insofar as we aimed at replicating the effect of scaffolding self-explanation prompts.

In both experiments, probability theory was chosen as the learning domain (cf. section 1.3). Furthermore, we used very similar learning and testing materials – making across-experiment comparisons possible. As learning outcomes, procedural knowledge (problem-solving performance) and conceptual knowledge (knowledge about the rationale of a solution procedure) were assessed (for more information on the learning outcome measures please see section 4.5.3 and 5.5.3).

Overall, this dissertation seeks to establish what works (i.e., to determine which features foster learning), to explain how it works (i.e., analyzing the learning processes), and to consider where and for whom it works (i.e., analyzing the effects on different learning outcomes and of different participants).

In the following, the main research questions of this dissertation are elaborated:

1. **To what extent do open and scaffolding self-explanation prompts as help procedures for integrating and understanding multiple representations foster high-quality self-explanations as well as conceptual and procedural knowledge?**

The quality of self-explanations is a major determinant of learned contents from studying worked-out examples (Roy & Chi, 2005). However, most learners' self-explanations on worked-out examples are far from being optimal (Renkl, 1997). This suggests that self-explaining has to be instructionally supported by prompting (Renkl, 2005). However, even when prompted, the quality of self-explanations remains variable indicating that it is difficult for some learners to engage in this activity (Roy & Chi). The latter was also confirmed by an own pilot study in which the experimental materials of Experiment 1 were used. In this pilot study, we analyzed the effects of open self-explanation prompts that consisted of questions on the interrelations between the tree-diagram and the arithmetical equation as well as their relations to the domain. It turned out that the learners (N = 6) had severe difficulties in answering them. Oftentimes they just did not know the answer. Particularly, they were not able to match important relations between the two representations when they received open self-explanation prompts. Specifically, they had severe difficulties in making use of the tree diagram for understanding the multiplication rule. These deficits in the self-explanations can lead to incomplete or incorrect knowledge, which, in the worst case, can severely impede further learning. Thus, there is evidence that some learners may profit from stronger instructional support than open self-explanation prompts are able to provide. Prompts that include some form of scaffolding are a promising starting point. Consequently, as a first step it was necessary to develop and experimentally test in Experiment 1 a *scaffolding-prompting* procedure to optimize self-explanations on relations included in the multiple representations. Thereby, deep-level conceptual knowledge with a focus on understanding should be fostered. In sum, Experiment 1 was conducted to test the effects of using open self-explanation prompts and scaffolding self-explanation prompts in order to foster learning from multi-representational worked-out examples.

2. **Do multiple representations foster high-quality self-explanations as well as conceptual and procedural knowledge, and do instructional support measures on integrating and understanding multiple representations (i.e., integration help and scaffolding self-explanation prompts) have additive effects?**

Multiple representations can provide unique benefits when learners are trying to gain a deep understanding (Ainsworth, in press). Regrettably, many studies have shown that this promise is not always achieved. Often, learners are overwhelmed with the complex demands of integrating and understanding multiple representations. This suggests that learners might profit from learning with multiple representations to a larger extent when instructional support measures that reduce load which is not related to processes of learning (cf. Ayres & Sweller,

2005) and increase learning-related processing are employed. For reducing load that is not related to processes of learning, an integration help with a combined color-flashing procedure (cf. Jeung et al., 1997; Kalyuga et al., 1999) was included in the worked-out solutions to facilitate the mapping between representations (cf. section 2 and section 5.5.1). To increase learning-related processing, scaffolding self-explanations prompts on integrating and understanding the multiple representations were implemented (cf. section 2 and section 5.5.1). In sum, in Experiment 2, the effects of multi-representational vs. mono-representational solutions, of an integration help, and of scaffolding self-explanation prompts on the understanding of probability theory (specific topic: complex events) were investigated.

The findings of Experiment 1 were taken up insofar as scaffolding self-explanation prompts which proved to be effective with respect to conceptual and procedural knowledge were implemented in Experiment 2.

4. Experiment 1: Scaffolds for Self-Explanation Lead to Meaningful Learning

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 from multi-representational resources when different information formats have to be integrated. Experiment 1 of this dissertation takes up the assumption of Roy and Chi and analyzes the effects of different types of self-explanation prompts when learning from multi-representational worked-out examples.

4.1 Learning with Multi-Representational Examples

As already mentioned, multiple representations are 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, in press; Ainsworth, Bibby, & Wood, 2002). Furthermore, it is expected that if learners are provided with a rich source of different representations of a domain, they build references across these representations (Ainsworth, in press).

According to a functional taxonomy of Ainsworth (in press), multiple representations are provided for three main purposes: (1) to support different ideas and processes, (2) to constrain representations, and (3) to promote a deeper understanding (for more detailed explanations see section 2). The last aspect was the focus of the present study.

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). This is due to the fact that learners are faced with complex learning demands when they are presented with a novel multi-representational system (Ainsworth, in press). Particularly, learners experience difficulties to learn how the representations relate 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 positive effects that were intended by the use of multiple representations do not occur to the extent expected (e.g., Ainsworth et al., 1998).

On the one hand, multiple representations offer unique possibilities of fostering understanding. On the other hand, they impose high demands on the learners. What could be a sensible solution?

One step towards a solution to the problem that multiple representations can impose cognitive overload may be to use a learning approach which reduces demands on the learners (cf. section 1.2). One such effective learning method is learning from worked-out examples (for a detailed description of this learning method see section 1.2). This learning method's reduction in cognitive load (e.g., Renkl, 2005; Sweller, 2005; Sweller et al., 1998) allows for an opportunity to use this free cognitive capacity for integrating and deeply understanding multiple representations (cf. also Schuh, Gerjets, & Scheiter, 2005).

As already explained in section 1.2, worked-out examples consist of a problem formulation, solution steps, and the final solution itself (cf. Figure 1 in section 2). Learning from worked-out examples is a very effective method for initial cognitive skill acquisition in well-structured domains such as mathematics (for an overview, see Atkinson, Derry, Renkl, & Wortham, 2000; Renkl, 2005) because the learners are unburdened from independent problem-solving. Thereby – in terms of the cognitive load theory (cf. section 1.2) – extraneous load (load not directly relevant to learning) is reduced (cf. Paas, Renkl, & Sweller, 2003; Renkl, 2005; Sweller, 2005). In fact, various researchers suggest that only when learning materials do not impose too high cognitive load, learners can engage in resource-demanding activities such as self-explanation or interrelating multiple representations (e.g., Mayer, Heiser, & Lonn, 2001; Moreno & Mayer, 1999). Thereby, the learners can concentrate on understanding the solution (which can be presented in a multi-representational format) and the underlying principles. Thus, *germane load* (load imposed by processes aimed at acquiring understanding) is enhanced.

4.2 Self-Explaining Worked-Out Examples

It is nevertheless important to note that the employment of worked-out examples does not necessarily lead to an enhancement of germane load. In fact, the quality of learning processes and learning outcomes strongly depends on the learners' self-explanation. As mentioned in 1.2, self-explanations are explanations provided by learners and mainly directed to themselves (Renkl, 2005). They contain information that is not directly given in the learning materials and that refer to solution steps and the reasons for them. The classical study on self-explanations of Chi and colleagues (Chi et al., 1989) analyzed individual differences with respect to how intensively learners self-explained the solution steps of worked-out examples (from the domain of physics). They found that learners who explained the worked-out examples more actively to themselves learned more. Renkl (1997) showed that even when the study time was held constant, self-explanation activity was related to learning outcomes. Thus, the depth to which learners engage in self-explanation is a significant predictor of the learners' ability to develop deep meaningful understanding of the material studied (Roy & Chi, 2005).

The role that self-explanation can play in multi-representational understanding has also been considered (cf. Roy & Chi, 2005). Aleven and Koedinger (2000) argue that self-explanations prove 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 & Loizou, 2003). However, learners show clear individual differences in processing worked-out examples. Most learners do not actively self-explain worked-out examples, that is, they do not productively use their free cognitive capacity for germane load (Renkl, 1997). This suggests that self-explaining has to be instructionally supported (Renkl, 2005) by making the link between representations salient (e.g., by an integrated format or by selecting the same color for corresponding parts in different representations) and by prompting self-explanations.

In sum, the quality of self-explanations is a major determinant of learned contents from studying worked-out examples. As many learners do not spontaneously engage in productive self-explanation activities, they have to be supported in this respect.

4.3 Instructional Support for Self-Explaining

Chi, de Leeuw, Chiu, and Lavancher (1994) found that spontaneous self-explanations during worked-out example study were not as effective as self-explanations that were enhanced by prompting (see also Renkl, Stark, Gruber, & Mandl, 1998). Prompts are requests that require the learners to process the to-be-learned contents in a specific way (Renkl, 2005; cf. also Berthold et al., 2006). They elicit self-explanation activities that the learners are capable of but do not show unpremeditated (Pressley et al., 1992). In order to account for the prompted self-explanation effect, it is necessary to make the assumption that learners are often not aware of gaps in their knowledge, unless they are explicitly prompted to reflect on their understanding (Chi, 2000). Thereby, they self-diagnose their knowledge gaps, and these gaps can be filled in by the learner, if there is enough support in the learning environment. Thus, through prompting, the learners are encouraged to induce the omitted information.

Learners benefit by self-explanation prompts provided by humans (Chi et al., 1994) and by computers (Aleven & Koedinger, 2002). Atkinson, Renkl, et al. (2003) showed that prompting principle-based self-explanations in a computer-based learning environment providing worked-out examples led to favorable learning outcomes in terms of performance on similar problems and novel problems in the domain of probability. They requested the learners to select the probability principle underlying a solution step from a list at each worked-out step. After selecting a principle, the correct one was displayed so that the learners received feedback. Further evidence for the positive effects of self-explanation prompting when learning from computer-based worked-out examples were provided, for example, by Conati and VanLehn (2000) as well as by Schworm and Renkl (2006a, b). Thus, it is sensible to design prompts that foster self-explanations in order to ensure that the free capacity that is available for studying multi-representational examples is effectively used for integrating and understanding representations.

However, even if prompted, the use of high-quality self-explanations remains variable, indicating that it is difficult for some learners to engage in this activity (Chi et al., 1989; Renkl, 2002; Roy & Chi, 2005). An own pilot study (cf. section 3) confirmed these difficulties of the learners. In this pilot study, we analyzed the effects of open self-explanation prompts (open questions inducing self-explanations, e.g., “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 just did not know the answer.

Thus, relying only on self-explanations has several disadvantages – even when self-explaining is elicited by prompts. The quality of the self-explanations elicited by self-explanation prompts is in many cases far from optimal. Sometimes the learner is not able to self-explain a specific solution step (cf. pilot study). Furthermore self-explanations can be fragmented (Roy & Chi, 2005). Finally, sometimes the 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, there is evidence that some learners may profit from stronger instructional support than open self-explanation prompts are able to provide (cf. Roy & Chi).

Prompts that include some form of scaffolding are a promising starting point. Collins, Brown, and Newman (1989) refer to scaffolding as a support for the learners that relieve them of parts of an overall task that the learners cannot yet manage (e.g., explaining difficult parts of a worked-out example). According to Vygotskian approaches, scaffolding 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 sensible to support learners by scaffolding on knowledge construction that would be out of reach for the learners without assistance. The intention is, however, to hand over responsibility to the learners as soon as possible. The latter implies a fading process which consists of the gradual removal of support until students are working on their own.

Yet, previous studies on various scaffolding 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 – including also self-explanations of the tutee – resulted in tutees' deep understanding. Hilbert, Schworm, and Renkl (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. However, the transition from instructional explanations to self-explanation prompts was equally effective as giving only self-explanation prompts. Thus, constructing an effective scaffolding method is not a trivial task. Nevertheless, there are experiments that successfully employed self-explanation prompts that included scaffolding support in form of menus providing "building blocks" of self-explanations (Aleven & Koedinger, 2002; Conati & VanLehn, 2000). However, theses studies did not experimentally compare different types of self-explanations prompts (e.g., with and without scaffolds).

4.4 Overview of Experiment 1 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 scaffolding may bring to bear the advantages of learning with multiple representations. Based on the assumption that scaffolding supports knowledge construction that would be out of reach for the learners without assistance, scaffolding 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 scaffolding self-explanation prompts (first fill-in-the-blank self-explanations, then open questions). 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 is a solution procedure applied in this way). Specifically, the following hypotheses were tested:

1. Self-explanation prompts (scaffolding and open) foster high-quality self-explanations on multi-representational examples.

2. Scaffolding self-explanation prompts have additional effects on high-quality self-explanations when compared to open self-explanation prompts.

3. Self-explanation prompts (scaffolding and open) foster procedural knowledge acquired from multi-representational examples.

4. Scaffolding self-explanation prompts have additional effects on procedural knowledge when compared to open self-explanation prompts.

5. Self-explanation prompts (scaffolding and open) foster conceptual knowledge acquired from multi-representational examples.

6. Scaffolding self-explanation prompts 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. Thus, we were especially interested in factors which enhance the conceptual understanding of the multiplication rule.

4.5 Methods

In the following the sample and design of Experiment 1 are presented. Furthermore, the procedure and the instruments are introduced.

4.5.1 Sample and Design

The participants of this study were 42 female and 20 male psychology students at the University of Freiburg, Germany. The mean age was about 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: “No self-explanation prompts” (*n* = 20), “open self-explanation prompts” (*n* = 22), and “scaffolding self-explanation prompts” (*n* = 20).

In a computer-based learning environment (for a detailed description see section 2), all learners studied four pairs of isomorphic worked-out examples (i.e., eight examples in total). The worked-out examples were presented with multi-representational solution procedures: a pictorial, tree-like solution and an arithmetical solution (see Figure 1 in section 2). All learners were supported in integrating the information from the tree (e.g., the ramifications) with the respective arithmetical information (e.g., the multiplication signs). This was accomplished by an integration help with a combined flashing-color-coding procedure (cf.

section 2). Additionally, participants of the condition scaffolding self-explanation prompts received self-explanations that consisted of questions (e.g., “Why do you calculate the total acceptable outcomes by multiplying?”). In the first worked-out example of each pair of isomorphic examples, the answers were provided in the form of fill-in-the-blank self-explanations (e.g., “There are ... times ... branches. Thus, all possible outcomes are included.”). In following isomorphic examples this support was faded out, and the participants received open self-explanation prompts. The answers had to be typed into corresponding boxes. In the condition open self-explanation prompts, the learners were provided with open self-explanation prompts only (e.g., open answer to “Why do you calculate the total acceptable outcomes by multiplying?”). The condition no self-explanation prompts (control condition) included no additional support; the learners were only provided with a text box for note-taking.

4.5.2 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 the scaffolding self-explanation prompts, open self-explanation prompts, or no self-explanation prompts. Finally, the participants completed a post-test on procedural and conceptual knowledge.

The experiment lasted approximately two hours (M = 128.63 minutes, SD = 31.30). The learning time (i.e., time spent on the worked-out examples) was significantly higher in the conditions with self-explanation prompts, $t(60) = 5.65$, $p < .001$ (Scaffolding self-explanation prompts: $M = 73.80$ minutes, $SD = 20.00$; Open self-explanation prompts: $M = 79.41$ minutes, $SD = 21.62$; No self-explanation prompts: $M = 46.25$ minutes, $SD = 17.68$). The two conditions 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: $r = .12$ between learning time and procedural knowledge; $r = .17$ between learning time and conceptual knowledge. Thus, the variable learning time was not included in further statistical analyses.

4.5.3 Instruments

Pretest: Assessment of prior knowledge. A short pretest on complex events containing six problems examined the topic-specific prior knowledge of the participants. An example for a 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 conditions, the written responses to the prompts were analyzed in detail. As Schworm and Renkl (2006a) 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 & 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 highest-quality self-explanations about the rationale of a principle. Thus, rationale-based self-explanations exceed principle-based self-explanations by giving reasons 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 helpful 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 reasoning about why a certain applicable principle has to be applied.

The coding categories were distinct. In the scaffolding self-explanation prompts condition the learners filled in the scaffolds 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 the annotations in the text boxes of every second isomorphic example in order to assure comparability between conditions (in any case empty boxes had to be filled in).

The written self-explanations of six participants were coded by a student research assistant and the author of this dissertation. 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 author of this dissertation 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 author of this dissertation.

Post-test: Assessment of learning outcomes. The learning outcomes were measured by a post-test that contained 14 problems. These problems were not identical to the pretest problems. Most of these post-test problems were more difficult than the pretest items. Seven post-test problems assessed procedural knowledge, seven problems required conceptual knowledge.

(1) Procedural knowledge (Problem-solving performance). The procedural knowledge problems referred to actions or manipulations that are valid within a domain (de Jong & Ferguson-Hessler, 1996). An example would be the multiplication of two fractions to calculate the probability of a complex event. This category included four near transfer items (same structure as the worked-out examples presented for learning but different surface features, such as the cover story) and three far transfer items (different surface features and also different structures, which means that a modified solution procedure had to be found). An example of a near 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.

(2) Conceptual knowledge. Conceptual knowledge problems referred to knowledge about facts, concepts, and principles that apply within a domain (de Jong & 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 on 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 the 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).

4.6 Results

Table 1 presents the means and standard deviations for the three experimental groups on the pretest, on principle-based self-explanations and rationale-based self-explanations, as well as on procedural and conceptual knowledge. Additionally, 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, Rosnow, & Rubin, 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 scaffolding self-explanation group with the open self-explanation group. The latter accounted for additional effects of the scaffolding 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 about .20 as weak effect, values of about .50 as medium effect, and values of about .80 or bigger as large effect (cf. Cohen, 1988; pp. 285–287).

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.

Table 1

Means and Standard Deviations (in Parentheses) on the Pretest, on the Self-Explanation Measures, and on the Learning Outcome Measures

	Pretest	Principle-based explanations	Rationale-based explanations	Procedural knowledge	Conceptual knowledge	Multiplication rule
No self-explanation 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)
Scaffolding 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)

4.6.1 Effects of Self-Explanation Prompts on Self-Explanations

Descriptively (cf. Table 1), higher means for principle-based self-explanations emerged in the groups with self-explanations prompts (scaffolding self-explanation prompts and open self-explanation prompts). As mentioned above, to test this difference, we aggregated the two groups with self-explanation prompts and compared them with the no-prompts group (control group). A *t* test yielded a significant and very strong difference for principle-based self-explanations in favor of the self-explanation prompts conditions, $t(59) = 7.63$, $p < .001$, $d = 2.08$ (due to technical problems, a process dataset of one participant in the condition 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 condition. A *t* test on potential additional effects of scaffolding 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 conditions with self-explanation prompts did not significantly differ in their principle-based self-explanations. In summary, scaffolding and open self-explanation prompts fostered such 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-explanations prompts (scaffolding self-explanation prompts and open self-explanation prompts) (cf. Table 1). A *t* test revealed a significant and strong difference for rationale-based self-explanations in favor of the (aggregated) self-explanation prompts conditions, $t(41) = 5.93$, $p < .001$, $d = 1.29$ (*t* test for unequal variances). A *t* test on additional effects of scaffolding self-explanation prompts on rationale-based self-explanations yielded a significant and strong effect in favor of the scaffolding 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, scaffolding 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, scaffolding and open self-explanation prompts were effective. Evidently, particularly scaffolding self-explanation prompts elicited this type of self-explanations.

4.6.2 Effects of Self-Explanation Prompts on Learning Outcomes

As Table 1 shows, we obtained higher means for procedural knowledge in the groups with self-explanations prompts (scaffolding self-explanation prompts and open self-explanation prompts). To test this difference, the (aggregated) groups with self-explanation prompts were compared to the no-prompts group (control group). A *t* test yielded a significant and medium to strong difference for procedural knowledge in favor of the self-explanation prompts conditions, $t(60) = 2.62$, $p = .005$, $d = .68$. Hence, 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 scaffolding 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 conditions with self-explanation prompts did not differ with respect to procedural knowledge. In summary, with respect to procedural knowledge, scaffolding and open self-explanation prompts fostered procedural knowledge. Yet, 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 scaffolding self-explanation prompts condition, 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 conditions outperformed their counterparts of the no-prompts condition with respect to conceptual knowledge. A *t* test contrasting the scaffolding 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, scaffolding self-explanation prompts had additional effects on conceptual knowledge in comparison to open self-explanation prompts.

A special focus of our learning environment was to understand *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. Therefore, we tested whether scaffolding and open self-explanation prompts fostered understanding of the multiplication rule. Descriptively, we obtained the highest mean in the scaffolding self-explanation prompts condition, whereas the means of the open self-explanation prompts and no-prompts conditions 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). Thus, the participants of the conditions with self-explanation prompts outperformed their counterparts of the no-prompts condition with respect to understanding the multiplication rule. A *t* test on the question of whether scaffolding 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). Hence, the overall pattern of performance indicated that above all scaffolding 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 scaffolding 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 mainly ascribed to the scaffolding self-explanation condition.

4.6.3 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 (cf. section 4.6.1 and section 4.6.2), the question arises whether the principle-based self-explanations mediated the effects on procedural knowledge. Furthermore, the scaffolding prompts version in particular elicited rationale-based self-explanations *and* fostered conceptual knowledge (cf. section 4.6.1 and section 4.6.2). This finding suggests that conceptual knowledge was fostered *via* rationale-based self-explanations. Posed as 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 indeed *mediated* the influence of the independent variable *prompts* (self-explanation prompts vs. no prompts) on procedural knowledge, three regression equations were estimated and tested for significance following the procedures suggested by Baron and Kenny (1986). In order to establish mediation, (1) the independent variable (i.e., prompts) must influence the dependent variable (i.e., procedural knowledge), (2) the independent variable (i.e., prompts) must influence the potential mediator (i.e., principle-based self-explanations), and (3) the influence 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.

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), this pattern of results indicates mediation. In order to directly test whether the mediation effect differed significantly from zero, we used the procedure suggested by MacKinnon (2002; see also MacKinnon & Dwyer, 1993). This test procedure includes 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 $a*b$, $se_{ab} = \sqrt{(a^2*[se_b]^2+ b^2*[se_a]^2)}$. 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 if rationale-based self-explanations mediated the influence of the independent variable *scaffolding prompts vs. 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 (scaffolding prompts vs. 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 (scaffolding prompts vs. 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 (scaffolding prompts vs. 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 scaffolding prompts vs. 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 scaffolding prompts on conceptual knowledge. Conclusively, the scaffolding prompts fostered conceptual knowledge because the scaffolding prompts effectively supported the learners in generating rationale-based self-explanations.

4.7 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 (scaffolding and open) foster principle-based self-explanations and rationale-based self-explanations. With respect to rationale-based self-explanations, scaffolding self-explanation prompts are especially effective. (b) Self-explanation prompts foster procedural and conceptual knowledge in multi-representational learning. This result adds to the growing body of evidence that shows that prompting self-explanations is crucial with respect to learning outcomes in example-based learning. (c) With respect to fostering principle-based self-explanations and procedural knowledge, it is equally effective to use open or scaffolding 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, scaffolding self-explanation prompts are especially effective. Rationale-based self-explanations mediated the effects on conceptual knowledge. (e) Scaffolding 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 scaffolding prompts particularly support the integration of multiple representations.

The present findings confirm the assumption of Roy and Chi (2005) that self-explanations are suited for integrating multiple representations and, thereby, foster learning outcomes. In comparison to other procedures of integration help such as the use of an integrated format, the employment of self-explanations prompts have the advantage that they go beyond the surface level with respect to the integration of different representations. They require the learner to focus on the *conceptual* correspondences (cf. Seufert & 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.

However, the question arises as to why scaffolding self-explanation prompts in particular were effective 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 scaffolding self-explanation prompts (as opposed to open self-explanation prompts) were shown to be effective with respect to the elicitation of rationale-based self-explanations and conceptual knowledge may be related to the zone of proximal development (Vygotsky, 1978). The scaffolding self-explanation prompts fostered the integration of the multiple representations, highly demanding self-explanations, and the conceptual understanding that was all slightly out of reach for learners without this assistance. 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. These prompts were only capable of eliciting self-explanations that the learners were capable of but spontaneously did not show – 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 they needed to integrate and to conceptually understand the multi-representational examples (e.g., “There are ... times ... branches. Thus, all possible outcomes are included.”). Conceptual understanding refers in particular to a deep understanding of the rationale of (multi-representational) solution procedures. Evidently, the scaffolds supported the learners in the troublesome process of looking behind the multi-representational solutions. As a consequence, our findings suggest that scaffolding self-explanation prompts should be provided if understanding the learning contents is slightly out of reach for learners without assistance. We call this the *scaffolding self-explanation effect* which refers to the elicitation of high-quality self-explanations and the acquisition of deep understanding.

Our findings suggest that scaffolding self-explanation prompts have to be provided if understanding the learning contents is slightly out of reach for learners without this assistance. Yet, to diagnose the dimensions of the zone of proximal development is a difficult task (Ainsworth et al., 1998). Nevertheless, we should be able to identify its lower boundary by analyzing the learner's unscaffolded performance. With this information, it should be possible to construct scaffolding 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 scaffolding self-explanation prompts for learners at different levels of skill acquisition (cf. Conati & VanLehn, 2000). Furthermore, self-explanations could be diagnosed online in order to provide an immediate and dynamic adaptation of scaffolding procedures (e.g., Aleven, Popescu, & Koedinger, 2001).

A last question that is raised refers to the generalizability of the present results. We have shown the use of (scaffolding) self-explanations 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 & Chi, 2005), we conjecture that it is appropriate to generalize the present findings across different learning contents. Regardless, an empirical test of this conjecture is necessary in future studies.

5. Experiment 2: Multiple Representations, an Integration Help, and Scaffolding Self-Explanation Prompts All Foster Understanding

Multiple representations (e.g., an arithmetical equation and a pictorial tree diagram) in learning materials provide unique benefits when learners are to gain a deep understanding. Often, however, multiple representations do not lead to the expected results because the (weaker) learners are cognitively overloaded, and they do not integrate the information from the different representations (e.g., Moreno & Mayer, 1999). Due to such problems, it seems wise to instructionally support the integration and understanding of multiple representations. 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 (e.g., Renkl, 2005). Additionally, Roy and Chi (2005) argued that self-explanations are especially suited to foster learning when different information formats have to be integrated (cf. chapter 4). The present study took up these assumptions. We analyzed the effects of mono- and multi-representational solutions when learning from worked-out examples and an integration help in form of a flashing-color-coding procedure. Furthermore, the findings of Experiment 1 with respect to effective self-explanation prompts were taken up insofar as we aimed at replicating the effect of scaffolding self-explanation prompts.

5.1 Learning with Multiple Representations

The following section contrasts an optimistic view and a pessimistic view on learning with multiple representations.

5.1.1 The Optimistic View

Multiple representations are often employed in order to foster understanding. Especially, proponents of cognitive constructivism emphasize the importance of using multiple representations of concepts and information (Spiro, Feltovich, Jacobson, & Coulson, 1995). When new information is presented through more than one codality (i.e., representational systems) and processed in a variety of ways, cognitive structures become more complex and contain rich associations. In their cognitive flexibility theory, Spiro and his colleagues (e.g., Spiro & Jehng, 1990) argue that the ability to construct and switch between multiple representations is fundamental to successful learning. Mayer (2005a) describes a theory of multi-media learning, which states that learners acquire more knowledge when they receive multiple representations.

What are the specific benefits of multiple representations? By combining different representations with different properties, learners are not limited by the strengths and weaknesses of one particular representation (cf. Ainsworth, in press; Ainsworth et al., 2002). Representing concepts or procedures in a multi-representational format allows learners to construct an understanding that prepares them better for transfer, with each example and representation adding connections and perspectives that others miss (Sternberg & Frensch, 1993). Furthermore, teaching with more representations can facilitate and strengthen the learning process by providing several mutually referring sources of information (Kozma, Russell, Jones, & Marx, 1996). Thus, one affordance of multiple representations is to support learners in active knowledge construction (Roy & Chi, 2005).

It is expected that learners build references across different representations of a domain (Ainsworth, in press). Thus, the learners gain an understanding not only how individual representations operate and how they are embedded in the domain but also how the representations relate to each other. However, in order to benefit from multi-representational learning materials, the learners must actively construct a conceptual knowledge representation that relates and integrates different kinds of information from diverse sources and codalities into a coherent structure (Schnotz & Bannert, 2003). The opportunity to construct such rich integrated structures constitutes a unique contribution of multiple representations to learning. The learners can achieve insights that are difficult to achieve with a single representation.

Many of the expected benefits of multiple representations result from their integration and co-ordination. The ability to integrate different representational formats is a characteristic of expertise (e.g., Kozma, Chin, Russell, & Marx, 2000). According to Ainsworth (in press), multiple representations can have three main functions: (1) to support different ideas and processes, (2) to constrain representations, and (3) to promote a deeper understanding (for detailed information see section 2). The latter aspect is focused in the present study.

5.1.2 The Pessimistic View

As already mentioned in section 4.1, a major problem of employing multiple representations is that often the expected learning outcomes do not occur (e.g., de Jong et al., 1998). This is due to the fact that learners are faced with complex learning demands when confronted with multi-representational system (Ainsworth, in press): (a) They must learn the format and operators of each representation, (b) understand the relation between each representation and the domain it represents, and (c) learn how the representations relate to each other. Particularly the latter demand is difficult for learners. Frequently they just concentrate on one type of representation or fail to link different representations to each other so that the intended positive effects do not occur (e.g., Ainsworth et al., 1998). In addition, guiding learners to coordinate multiple representations has been found to be far from trivial (de Jong et al., 1998).

For instance, Tarmizi and Sweller (1988) presented learners multi-representational solutions (a graphical representation, e.g., a depicted triangle, and an arithmetical representation, e.g., computation of an angle). When the two external representations were – as usual – presented separately from each other, the learners had to devote many cognitive resources in order to mentally integrate them. This demand imposed a heavy cognitive load and hindered learning.

In sum, the optimistic stance suggests that learning with multiple representations offers unique possibilities of fostering understanding. The pessimistic stance suggests that multiple representations impose (too) high demands on the learners. An important step toward the solution of the problem that multiple representations can impose cognitive overload may be to use a learning approach that reduces load (cf. section 1.2).

5.2 Multiple Representations in Worked-Out Examples: Supporting the Integration

One such method that is load-saving and nevertheless effective is learning from worked-out examples (Renkl, Gruber, Weber, Lerche, & Schweizer, 2003; see also Paas & van Gog, in press; Renkl, 2005; Sweller et al., 1998). It provides opportunity to use free cognitive capacity for integrating and understanding multiple representations (cf. also Schuh et al., 2005).

As already explained in section 1.2 and section 4.1, learning from worked-out examples is a very effective method for initial cognitive skill acquisition in well-structured domains such as mathematics (cf. Atkinson et al., 2000; Renkl, 2005) because the learners are relieved from finding a solution on their own (cf. section 1.2). Thereby – in terms of the cognitive load theory – extraneous load (load not directly relevant to learning) is reduced (cf. Paas, Renkl, et al., 2003; Renkl, 2005).

Mayer and colleagues (e.g., Mayer et al., 2001; Moreno & Mayer, 1999) argue that only if the learning materials do not impose too high extraneous cognitive load, learners are able to engage in resource-demanding activity such as self-explanations or interrelating multiple representations. For instance, as previously outlined, Tarmizi and Sweller (1988) presented multi-representational problems from the domain of geometry that were to be solved in one condition and worked-out examples in the other condition. In this case, they did not find the usual advantage of worked-examples. Does this mean that there is no *example effect* in learning with multiple representations? Definitely not. The authors explained this finding by the fact that the two information sources (graphical, e.g., a depicted triangle, and arithmetical, e.g., computation of an angle) were not integrated, and the learners had to devote many cognitive resources in order to mentally relate these sources to each other which imposed a heavy extraneous load. This phenomenon was labeled the split-attention effect (Ayres & Sweller, 2005). Thereby, the *resource-saving* effect of learning from worked-out example was countermanded. However, worked-out examples in which the multiple representations were spatially integrated (integrated format) enhanced learning in comparison to conventional problem solving and split-source examples. These findings were replicated by Ward and Sweller (1990) for physics examples and by Mwangi and Sweller (1998) for examples of mathematical word problems. By placing corresponding aspects of the representations next to each other, cues for integration are available and learners do not have to waste cognitive processing by scanning around the page (Ayres & Sweller; Mayer, 2005c). Besides physical integration, color codes can reduce search efforts and thus produce similar effects as spatial contiguity (Folker, Ritter, & Sichelschmidt, 2005; Jeung et al., 1997; Kalyuga et al., 1999). Color provides orientation and reduces search processes, thus leading to an enhanced integration process (cf. Kalyuga et al.). Moreover, computer-based learning environments offer the possibility of flashing in order to help students build connections among multiple representations (e.g., Mayer, 2005c). Thereby the learner’s attention can be directed towards the corresponding parts in the different representations. Techniques such as flashing and color-coding are especially appropriate when elements in one representation do not correspond to certain, well-circumscribed parts in the other representation; in this case no spatial one-to-one allocation is possible (Renkl, 2005).

In a nutshell, it is important to avoid formats that require learners to split their attention between multiple representations that are difficult to integrate (Ayres & Sweller, 2005). Instead, multi-representational solutions should be combined with instructional techniques such as integrated format, color-coding, or flashing so that the mapping between representations becomes easier. Thereby, the need for learners to extensively engage in search processes in the multiple representations is obviated (Ayres & Sweller; cf. Renkl, 2005: easy-mapping principle). By reducing visual search processes, resources for productive learning processes such as self-explanations are freed. Thereby, the learners can concentrate on understanding the solution (which can be presented in a multi-representational format) and the underlying principles. Thus, germane load (Sweller et al., 1998) (load imposed by processes aimed to gain understanding) is enhanced.

5.3 Scaffolding Self-Explaining

As already explained in section 4.2, it is, however, important to note that the employment of – even well-designed – worked-out examples does not necessarily lead to effective self-explanations and learning: Learners show clear individual differences in processing worked-out examples (for more detailed information on self-explanations see section 4.2). This suggests that self-explaining has to be instructionally supported (Renkl, 2005) by making the link between representations salient (e.g., integrated format) and by prompting self-explanations (cf. section 4.3).

However, even when self-explanations are prompted, their quality is in many cases far from being optimal (Chi et al., 1989; Renkl, 2002; Roy & Chi, 2005). Sometimes the self-explanations are only partially correct or even incorrect (Renkl, 2002). This can lead to incomplete or incorrect knowledge that can severely impede further learning.

In contrast, Chi (2000) assumes on the basis of respective empirical analyses that incorrect self-explanations are harmless. According to Chi et al. (1989), generating incorrect self-explanations can even create an opportunity for cognitive conflicts which lead to self-explanation episodes resolving these conflicts (cf. 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 argue 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 (cf. section 4.3). In Experiment 1 (cf. chapter 4), we compared the effects of three conditions when self-explaining multi-representational worked-out examples from the domain of probability: scaffolding self-explanation prompts (fill-in-the-blank self-explanations and then open self-explanations), open prompts (right from the beginning), and no self-explanation prompts (Berthold & Renkl, 2005). Both types of self-explanation prompts fostered procedural knowledge (problem-solving performance). However, conceptual knowledge (knowledge about the rationale of a solution procedure) was particularly fostered by scaffolding self-explanation prompts (fill-in-the-blank explanations). The latter effect was mediated by self-explanations that do not only relate a solution step to an underlying principle but also explicate the rationale of the principle. Thus, for enhancing both procedural knowledge and conceptual understanding, scaffolding self-explanation prompts are best provided. We took up this finding in this Experiment 2 and employed scaffolding self-explanation prompts.

5.4 Overview of Experiment 2, Hypotheses, and Research Questions

Against the background of the preceding discussion, it can be argued that the employment of worked-out examples reduces extraneous cognitive load which enables the learners to use "free" cognitive capacity for the integration and understanding of multiple representations (cf. section 1.2). The free capacity may, in turn, bring to bear the advantages of learning with multiple representations. This should be especially true when support procedures such as an integration help or self-explanation prompts are employed. In this Experiment 2, the effects of multi-representational vs. mono-representational solutions, of an integration help in form of a flashing-color-coding procedure, and of scaffolding self-explanation prompts (replication of Experiment 1) on learning probability were investigated (specific topic: complex events). Conceptual knowledge (knowledge about the rationale of a solution procedure) and procedural knowledge (problem-solving performance) were assessed as learning outcomes. Specifically, we tested the following hypotheses:

1. Multi-representational examples foster conceptual knowledge and procedural knowledge.

2. An integration help in form of a flashing-color-coding procedure that is included in the multi-representational examples foster conceptual knowledge and procedural knowledge.

3. Scaffolding self-explanation prompts foster conceptual knowledge and procedural knowledge.

In addition, we addressed the following "two-sided" research questions.

4. To what extent do scaffolding self-explanation prompts actually foster different types of self-explanations? Do the type of representational examples (multi- vs. mono) and the integration help also influence self-explanation activity?

5. Are the (potential) effects on conceptual knowledge and procedural knowledge mediated by the type of self-explanations?

6. Does the type of representational examples (multi- vs. mono), an integration help, and scaffolding self-explanation prompts influence cognitive load during learning?

5.5 Methods

In the following the sample and design of Experiment 2 are presented. Afterwards, the procedure and the instruments are introduced.

5.5.1 Sample and Design

The participants of this study were 87 female and 83 male students from grades 10 and 11 of German gymnasiums (i.e., highest track in the German three-track system). The mean age was 16.21 years (*SD* = .91).

In an experiment with eight conditions, four mono-representational (pictorial or arithmetical representation) conditions and four multi-representational (pictorial and arithmetical representation) conditions were implemented (see Table 2): (1) “Pictorial solutions / no self-explanation prompts”, (2) “pictorial solutions / self-explanation prompts”, (3) “arithmetical solutions / no self-explanation prompts”, (4) “arithmetical solutions / self-explanation prompts”, (5) “pictorial and arithmetical solutions / no integration help / no self-explanation prompts”, (6) “pictorial and arithmetical solutions / no integration help / self-explanation prompts”, (7) “pictorial and arithmetical solutions / integration help / no self-explanation prompts”, (8) “pictorial and arithmetical solutions / integration help / self-explanation prompts". The four multi-representational conditions constituted a 2x2 design - Factor 1: integration help (with versus without); Factor 2: self-explanation prompts (with versus without). The participants were randomly assigned to each of the eight conditions.

Table 2

Design of the Experiment

	Scaffolding self-explanation prompts	No self-explanation prompts
Pictorial solutions	n = 21	n = 21
Arithmetical solutions	n = 21	n = 22
Pictorial and arithmetical solutions / no integration help	n = 21	n = 22
Pictorial and arithmetical solutions / integration help	n = 21	n = 21

In a computer-based learning environment (for a detailed description see section 2), all learners studied four pairs of isomorphic worked-out examples (i.e., eight examples in total). In the mono-representational conditions, a pictorial tree-diagram or an arithmetical equation was presented. In the multi-representational conditions, both a pictorial tree diagram and an arithmetical equation were provided in each example (see Figure 1). In two of the multi-representational conditions, the learners were supported in integrating the arithmetical information (e.g., the multiplication signs) and the information from the tree diagram (e.g., the ramifications) by an integration help.

Participants of the conditions with scaffolding self-explanation prompts received questions that should elicit self-explanations (e.g., “Why do you calculate the total acceptable outcomes by multiplying?”). In the first worked-out example of each pair of isomorphic examples, the answers were provided in form of fill-in-the-blank explanations (e.g., “There are ... times ... branches. Thus, all possible outcomes are included.”). In following isomorphic examples this support was faded out, and the participants received open self-explanation prompts. The answers had to be typed into corresponding boxes. The groups without prompts were just provided a text box in order to take notes.

5.5.2 Procedure

The 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 demographic questionnaire. Afterwards, the learners worked on a pretest. Then, they entered the learning environment. In order to provide or reactivate basic knowledge that allowed the participants to understand the following worked-out examples, an instructional text on basic principles of probability was provided. Afterwards, the participants studied eight worked-out examples. During this phase, the experimental manipulation was realized. After every second worked-out example, the participants were asked to answer six questions on cognitive load. Finally, the participants completed a post-test on procedural and conceptual knowledge.

The experiment lasted on average 151.97 min (SD = 28.31). The learning time (i.e., time spent on the worked-out examples) was approximately one hour (M = 55.99 min, SD = 18.87). With respect to this learning time, we found significant differences between the eight experimental conditions, $F(7, 169) = 10.55$, $p < .001$, $\eta^2 = .31$. Although learning time was related to learning outcomes in a statistically significant way, it accounted for very small portions of variance of the learning outcomes (1.3 % for conceptual knowledge, ß = 14, $t(169) = 1.82$, $p = .071$ and 3.3 % for procedural knowledge, ß = .20, $t(169) = - 2.60$, $p = .010$). Nevertheless, we used learning time as a covariate in cases where it significantly (5 % level) contributed to the learning outcomes in the respective ANCOVA models.

5.5.3 Instruments

Pretest: Assessment of prior knowledge. The pretest on complex events with twelve items examined the topic-specific prior knowledge of the participants. It included four simple items which assessed basic knowledge of probability theory (e.g., “You play a game with a dice, 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 of the Latin course (altogether 7 students) who are supposed to read aloud their translation. Stupidly, you have copied it from your friend. What is the probability that the two of you are allotted?”). The items were scored by zero points (incorrect answer) or by one point (correct answer). On the whole, 12 points could be achieved. This sum was divided by the number of items (12) so that the test score represented the percentage of items solved correctly.

Self-explanations: Assessment of learning processes. In all experimental groups, the written responses to the prompts or the annotations in the text boxes, respectively, were analyzed. The quality of written self-explanations is a good indicator of the quality of the learning processes (Schworm & Renkl, 2006a). Similar as in Experiment 1, the protocols were thoroughly examined for content segments that corresponded to the following high-quality 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 (cf. 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

the 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 was introduced in Experiment 1. It referred to self-explanations about the rationale of a principle. Rationale-based self-explanations exceed principle-based self-explanations by giving reasons why the principle is as it is. For that reason, for rationale-based self-explanations it was, for example, not enough to explain why one has to multiply in the sense of the correct application conditions of a principle (e.g., "Because it is AND.") but also *why* one has to multiply in the sense of providing a rationale of the principle itself (cf. also section 4.5.3).

(c) Incorrect self-explanations. This category was scored if the learner generated an incorrect self-explanation (e.g., misconcepts, confusion of two principles, or wrong elaboration of a principle).

The coding categories were distinct. In the conditions with scaffolding self-explanation prompts the learners filled in the scaffolds in the first worked-out example of each pair whereas the learners of the conditions without prompts just took notes. The statistical analyses in the Results section refer only to the written responses to the prompts or 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 six participants were coded by two student research assistants and the author of this dissertation. 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 author of this dissertation re-examined the protocols and made the final decision. As the inter-rater reliability was very good, the rest of the protocols were just coded by one rater.

Due to technical problems, the process datasets of ten participants were lost (two from the groups arithmetical solutions / no self-explanation prompts and pictorial and arithmetical solutions / no integration help / no self-explanation prompts respectively as well as one dataset of each of the other groups). Thus, the degrees of freedom are reduced by ten in the analyses including self-explanations.

Cognitive load questions: Assessment of cognitive demands. After every second isomorphic example, the learners were asked to answer six questions on various aspect of cognitive load on a 9-point rating scale (1 = lowest score, 9 = highest score). An example for a cognitive load item is: “How difficult is it for you to find the information you need in the learning environment?” (cf. Paas, Tuovinen, Tabbers, & van Gerven, 2003). For the analyses reported in the Results section, the scores of the six questions were aggregated.

Post-test: Assessment of learning outcomes. The post-test contained 23 problems. Most of these problems were more difficult than the pretest items. All items were scored by zero points (incorrect answer) or one point (correct answer). The post-test assessed the following knowledge types.

(1) Procedural knowledge (Problem-solving performance). The procedural knowledge problems referred to actions or manipulations that are valid within a domain, for example, multiplying two fractions to calculate the probability of a complex event (cf. de Jong & Ferguson-Hessler, 1996). This category included two open questions, 11 near transfer items (same structure as the worked-out examples presented for learning but different surface features, such as the cover story), and four far transfer items (different surface features and also different structure, which means that a modified solution procedure had to be found). An example of an open question is: “The ball baths of IKEA contains balls in different colors among which 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 got nine commensurate segments with different

pictures (among which 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 soap box competition. The winner receives 100 Euro, the second place finisher gets 50 Euro, and the third gets 25 Euro. The drivers of the soap boxes which finish fourth and fifth get consolation prices in the form of tickets for a hot springs. You 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 the 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?" On the whole, 17 points could be achieved. This sum was divided by the number of items (17) so that the test score represented the percentage of items solved correctly.

(2) Conceptual knowledge. 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 knowledge about the rationale of a solution procedure, that is, why the solution procedures are as they are. Thus, it included 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 the fractions have to be multiplied (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 tapped on the quality of representation integration. One point was assigned for a correct answer with a substantial degree of reasoning and elaboration. Other answers were scored with zero points. On the whole, 6 points could be achieved. This sum was divided by the number of items (6) so that the test score represented the percentage of items solved correctly.

5.6 Results

Table 3 presents the means and standard deviations of the pretest, principle-based self-explanations, rationale-based self-explanations, incorrect self-explanations, cognitive load, conceptual knowledge, and procedural knowledge in the eight experimental groups. For testing the hypotheses or addressing the research questions, we employed *F* tests. According to the recommendations of Rosenthal and Rosnow (1985; see also Rosenthal et al., 2000), we refrained from reporting overall ANOVA results when not motivated by respective research questions. Of particular interest were *F* tests comparing the (aggregated) multi-representational groups with the mono-representational groups, the groups with an integration help with the groups without an integration help, and the self-explanation groups with the no self-explanation groups. Furthermore, the multi-representational conditions were considered as a 2x2 design (with and without integration help; with and without prompts). An alpha-level of .05 was used for all statistical analyses. As an effect size measure, we used η^2 – qualifying values of about .01 as weak effect, values of about .06 as medium effect, and values of about .14 or bigger as large effect (cf. Cohen, 1988; pp. 285–287). With respect to the students' topic-specific prior knowledge, an ANOVA revealed no significant differences, $F(7, 168) = 1.29$, $p = .261$. Hence, there was no a priori difference between groups with respect to this important learning prerequisite.

Table 3

Means and Standard Deviations (in Parentheses) on the Pretest, on Self-Explanation Measures, on Cognitive Load, and on the Learning Outcomes

	Pretest	Principle-based explanations	Rationale-based explanations	Incorrect explanations	Cognitive load	Conceptual knowledge	Procedural knowledge
Pictorial / no self-explanation prompts	.46 (.16)	.50 (1.57)	.00 (.00)	.45 (.83)	3.56 (1.52)	.29 (.17)	.44 (.22)
Pictorial / self-explanation prompts	.41 (.21)	5.50 (2.19)	2.60 (2.91)	3.25 (2.20)	5.07 (1.52)	.40 (.19)	.35 (.15)
Arithmetical / no self-explanation prompts	.43 (.15)	.15 (.37)	.00 (.00)	.25 (.44)	3.55 (1.27)	.36 (.17)	.49 (.18)
Arithmetical / self-explanation prompts	.33 (.16)	5.60 (2.52)	1.85 (2.16)	2.95 (2.68)	4.25 (1.11)	.45 (.21)	.41 (.20)
Pictorial and arithmetical / no integration help / no self-explanation prompts	.45 (.20)	.15 (.37)	.00 (.00)	.85 (1.63)	2.87 (1.05)	.33 (.18)	.48 (.22)
Pictorial and arithmetical / no integration help / self-explanation prompts	.44 (.19)	4.70 (3.03)	2.55 (3.27)	2.20 (1.85)	5.06 (1.13)	.48 (.17)	.36 (.19)
Pictorial and arithmetical / integration help / no self-explanation prompts	.40 (.18)	.25 (.64)	.10 (.31)	.10 (.31)	2.62 (1.19)	.41 (.23)	.46 (.21)
Pictorial and arithmetical / integration help / self-explanation prompts	.46 (.19)	4.90 (2.53)	3.70 (3.20)	2.50 (1.91)	3.93 (1.33)	.59 (.19)	.49 (.21)

5.6.1 Effects on Learning Outcomes

Learners who received multi-representational solutions acquired significantly more conceptual knowledge than learners with just one representation, $F(1, 169) = 5.71$, $p = .018$, $\eta^2 = .033$ (small to medium effect). With respect to procedural knowledge, the groups with multi-representational solutions and with mono-representational solutions did not differ, $F < 1$ (learning time was included as a covariate; it significantly predicted procedural knowledge, $F(1, 169) = 6.60$, $p = .011$).

The participants in the multi-representational group who received an integration help outperformed the learners without such a help with respect to conceptual knowledge, $F(1, 169) = 4.57$, $p = .035$, $\eta^2 = .05$ (small to medium effect). With respect to procedural knowledge, we did not find a statistically significant difference, $F(1, 84) = 1.48$, $p = .227$ (learning time was included as a covariate; it significantly predicted procedural knowledge, $F(1, 169) = 5.21$, $p = .025$).

The scaffolding self-explanation prompts fostered conceptual knowledge, $F(1, 169) = 20.40$, $p < .001$, $\eta^2 = .11$ (medium to strong effect). We also found a significant effect on procedural knowledge, $F(1, 169) = 4.60$, $p = .033$, $\eta^2 = .03$ (small to medium effect) (in this case, the influence of learning time as a covariate did not reach the level of significance, $F(1, 169) = 2.97$, $p = .087$). However, it was a negative effect, that is, the prompts impeded the acquisition of procedural knowledge.

When considering the multi-representational conditions as a 2x2 design (with and without integration help; with and without prompts), the interaction between integration help and self-explanation prompts with respect to conceptual knowledge did not reach the level of significance, $F < 1$. The same was true with respect to procedural knowledge, $F(1, 81) = 2.37$, $p = .128$. Hence, the effects of the two instructional procedures did not depend on each other.

In sum, conceptual knowledge was fostered by multi-representational solutions, the integration help, and scaffolding self-explanation prompts. These results correspond fully to our corresponding hypotheses. Contrary to our expectations, scaffolding self-explanation prompts had a negative effect on procedural knowledge.

5.6.2 Effects on Self-Explanations

With respect to rationale-based self-explanations, we found a significant difference in favor of the scaffolding self-explanation prompts group, $F(1, 159) = 64.93$, $p < .001$, $\eta^2 = .29$ (strong effect). We also obtained a significant difference in favor of the scaffolding self-explanation prompts groups with respect to principle-based self-explanations, $F(1, 159) = 262.49$, $p < .001$, $\eta^2 = .62$ (strong effect). Hence, the scaffolding self-explanation prompts elicited more principle-based self-explanations and more rationale-based self-explanations when compared with the groups without self-explanation prompts. However, scaffolding self-explanation prompts also evoked significantly more incorrect self-explanations, $F(1, 159) = 74.88$, $p < .001$, $\eta^2 = .32$ (strong effect).

The groups with multi-representational and mono-representational solutions did not differ in their self-explanations, $F(1, 159) = 1.49$, $p = .224$ for rationale-based self-explanations; *F*s < 1 for principle-based self-explanations and incorrect self-explanations. Similarly, no significant differences were found with respect to the integration help, $F(1, 79) = 1.03$, $p = .314$ for rationale-based self-explanations, *F*s < 1 for principle-based self-explanations and incorrect self-explanations. When considering the multiple representations conditions as a 2x2 design (with and without an integration help; with and without prompts), the interaction effects between integration help and self-explanation prompts with respect to rationale-based self-explanations, $F(1, 80) = 1.05$, $p = .309$, principle-based self-explanations, $F < 1$, and incorrect self-explanations, $F(1, 80) = 2.25$, $p = .138$, did not reach the level of significance.

In sum, scaffolding self-explanation prompts fostered rationale-based self-explanations and principle-based self-explanations. However, they also evoked more incorrect self-explanations.

5.6.3 Mediation of the Learning Outcomes by Self-Explanations

We have established that self-explanation prompts evoked rational-based explanations, principle-based self-explanations but also incorrect self-explanations (cf. section 5.6.2) *and* that they fostered conceptual knowledge but hindered the acquisition of procedural knowledge (cf. section 5.6.1). Did the different types of self-explanations mediate the effects on conceptual and procedural knowledge? The pattern of results obtained so far suggested 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 other words, 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?

(a) Rationale-based self-explanations and principle-based self-explanations were substantially intercorrelated (r = .55, p < .001). In addition, we found significant correlations between rationale-based self-explanations and conceptual knowledge (r = .43, p < .001) as well as between principle-based self-explanations and conceptual knowledge (r = .43, p < .001). These latter correlations further supported the assumption of mediation. Thus, first we directly tested whether rationale-based self-explanations *mediated* the influence of the independent variable *prompts* (scaffolding self-explanation prompts vs. no prompts) on conceptual knowledge. Therefore, conceptual knowledge was regressed on the factor prompts and rationale-based self-explanations in a simultaneous multiple regression model. The mediation hypotheses would have been supported if the effect of the independent variable prompts was substantially reduced when the mediator was included as an additional predictor of the dependent variable (Baron & Kenny, 1986). This proved to be true. As expected, rationale-based self-explanations still predicted conceptual knowledge, ß = .37, $t(159) = 4.39$, $p < .001$, whereas the influence of the factor prompts was no longer significant, ß = .11, $t(169) = 1.33$, $p = .187$. In order to directly test whether the mediation effect differed significantly from zero, 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 + $error_1$ 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. Then the statistical significance of the mediation effect is determined: $z = a*b / se_{ab}$, with se_{ab} being the standard error of the mediation effect $a*b$, $se_{ab} = \sqrt{(a^2*[se_b]^2 + b^2*[se_a]^2)}$. In such an analysis, we obtained a *z* score of 3.88 that was significant on the 1% alpha. This finding supported the assumption that scaffolding self-explanation prompts fostered conceptual knowledge because they effectively supported the learners in generating rationale-based self-explanations.

Furthermore, we tested whether also principle-based self-explanations *mediated* the influence of the independent variable *prompts* (scaffolding self-explanation prompts vs. no prompts) on conceptual knowledge. As to expect in the case of mediation, in the simultaneous regression model principle-based self-explanations still predicted conceptual knowledge, ß = .48, $t(159) = 4.08$, $p < .001$, whereas the influence of the factor prompts was no longer significant, ß = -.07, $t(169) = .56$, $p = .579$. In the procedure of MacKinnon (2002), a *z* score of 3.00 that was significant on the 1% alpha level resulted. Thus, not only rationale-based self-explanations but also principle-based self-explanations were a crucial mediator with respect of acquiring conceptual knowledge.

When including *both* rationale-based self-explanations *and* principle-based self-explanations as mediators in a simultaneous regression model, rationale-based self-explanations, ß = .31, $t(159) = 3.64$, $p < .001$, and principle-based self-explanations, ß = .38, $t(159) = 3.28$, $p = .001$, still significantly predicted conceptual knowledge, whereas the influence of the factor prompts was no longer significant, ß = -.15, $t(159) = -1.33$, $p = .185$. Thus, the effect on conceptual knowledge was mediated by both rationale-based self-explanations and principle-based self-explanations.

(b) With respect to incorrect self-explanations and procedural knowledge, we obtained a significant correlation of $r = -.25$, $p = .001$. This finding – in addition to the significant effect of scaffolding self-explanation prompts on incorrect self-explanations *and* on hindering the acquisition of procedural knowledge – supported the assumption of mediation. In order to directly test whether incorrect self-explanations indeed *mediated* the influence of the independent variable *prompts* (scaffolding self-explanation prompts vs. no prompts) on procedural knowledge, procedural knowledge was regressed on the factor prompts and incorrect self-explanations in a simultaneous multiple regression model. As expected, incorrect self-explanations still predicted procedural knowledge, ß = -.25, $t(159) = -2.61$, $p = .010$, whereas the influence of the factor prompts was no longer significant, ß = -.01, $t(169) = -.14$, $p = .888$. In the procedure of MacKinnon (2002), a z score of -2.55 that was significant on the 1% 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 to more incorrect self-explanations.

5.6.4 Effects on Cognitive Load

Surprisingly, participants who had received mono-representational solutions reported a significant higher cognitive load than the learners in the multi-representational groups, $F(1, 159) = 4.26$, $p = .041$, $\eta^2 = .03$ (small to medium effect). The participants who were provided an integration help experienced significantly less cognitive load than their counterparts in the groups without such an integration help, $F(1, 79) = 4.33$, $p = .041$, $\eta^2 = .05$ (small to medium effect). In the groups with scaffolding self-explanation prompts, the participants experienced significantly more cognitive load than their counterparts in the groups without such prompts, $F(1, 159) = 45.75$, $p < .001$, $\eta^2 = .23$ (strong effect). When considering the multi-representational conditions as a 2x2 design (with and without an integration help; with and without scaffolding self-explanation prompts), the interaction between integration help and scaffolding self-explanation prompts with respect to cognitive load did not reach the level of significance, $F(1, 85) = 2.01$, $p = .160$. In sum, mono-representational solutions, learning without an integration help, and scaffolding self-explanation prompts increased cognitive load.

5.7 Discussion

We found the following main results. Conceptual knowledge was fostered by multi-representational solutions, the integration help, and scaffolding self-explanation prompts. Scaffolding self-explanation prompts had, however, a negative effect on procedural knowledge. With respect to self-explanations, scaffolding self-explanation prompts elicited rationale-based self-explanations as well as principle-based self-explanations but also incorrect self-explanations. Both rationale-based self-explanations and principle-based self-explanations mediated the effects of scaffolding self-explanation prompts on conceptual knowledge whereas the negative effect on procedural knowledge was mediated by incorrect self-explanations. Cognitive load was increased by mono-representational examples, by providing the multi-representational examples without an integration help, and by scaffolding self-explanation prompts.

5.7.1 Learning with Multi-Representational Examples: The Realistic View

Our findings neither support a totally optimistic stance on learning with multiple representations nor a totally pessimistic stance. Rather, we suggest adopting a *realistic view*: Multiple representations *can* be a powerful aid to teaching and learning – under specific conditions. Specifically, our realistic view on learning with multiple representations includes two main assumptions: (a) Not all knowledge types can be equally effectively enhanced by multiple representations. Evidently, this research showed that learning outcomes which especially benefit from the *integration* of multiple representations can be particularly enhanced by learning with multiple representations (i.e., conceptual knowledge). (b) Learning with multiple representations should be supported by instructional procedures: Our findings show that learners evidently profit from an integration help in form of flashing and color-coding and from scaffolding self-explanation prompts when learning with multiple representations. Obviously, the potential of learning with multiple representations can only be fully exploited when instructional support measures are implemented. Importantly, our findings extend the growing body of research showing that multi-representational learning environments which include instructional support measures are more effective than pure multi-representational learning arrangements without such support (cf. Moreno & Durán, 2004). Both assumptions of our realistic view are again taken up in the followings.

Multiple representations and an integration help foster conceptual knowledge but not procedural knowledge. Schnotz (2005) argues that the effects of certain multimedia (i.e., multi-representational) elements such as pictures in texts differ depending on the task that should be accomplished later on. Schnotz as well as Ainsworth (in press) assume that performance is best fostered when the structure of information required for a test problem corresponds with the information structure in the learning materials. Schnotz calls this rule the *structure-mapping effect*. Furthermore, Ainsworth (in press) stresses that it is only for certain functions and associated learning goals that learners should master the demanding cognitive task of translating between two representations. Against the background of these considerations, we conjecture that it was not necessary (though helpful; cf. Experiment 1) for the learners to integrate the different representations in order to reach the goal of learning how to solve problems (procedural knowledge). Reaching the goal of understanding the "why" of solution procedures, was, however, much more difficult without integrating the different representations. This conjecture is supported by the finding that both instructional procedures focusing on integration – integration help and self-explanation prompts – fostered performance on conceptual problems. In contrast, it might have been sufficient – even more parsimonious and in that sense appropriate – to just concentrate on the arithmetical equations for later problem solving. Only if the intended learning goals (e.g., conceptual understanding) require multiple representations, they should be provided, and learners should be supported in integrating them (e.g., Moreno & Durán, 2004).

Moreover, the learning goal and the required representations to achieve it should be explicitly stated. Otherwise, the learners might even spontaneously translate the single representation into other representations, whether necessary for the learning goal or not. In our study, this assumption was confirmed. We informally observed that learners who were provided mono-representational examples – especially in the conditions with tree diagrams – often spontaneously translated the representation into another representation (e.g., arithmetical equations). This translation might have caused the higher amount of cognitive load in the mono-representational conditions.

Similarly, the learners who received multi-representational examples without an integration help had to invest much effort in order to map the two representations onto each other, with the consequence of an increased cognitive load. Our finding that multi-representational examples without an integration help enhanced the level of cognitive load confirms the corresponding assumption of cognitive load theory (e.g., Ayres & Sweller, 2005).

Scaffolding self-explanation prompts elicit rationale-based self-explanations and principle-based self-explanations and thereby foster conceptual knowledge. These findings confirm the assumption of Roy and Chi (2005) as well as the findings of Experiment 1 (cf. Berthold & Renkl, 2005) that self-explanations are suited for enhancing understanding of multiple representations and, thereby, learning outcomes. The scaffolding self-explanation prompts fostered high-quality self-explanations and a conceptual understanding that both seemed to be slightly out of reach for learners without this assistance (cf. zone of proximal development; Vygotsky, 1978). In particular, the scaffolding self-explanation prompts stimulated learners to generate types of self-explanations (i.e., rationale-based self-explanations and principle-based self-explanations) that they rarely show spontaneously although they are very useful for learning. Conceptual knowledge refers in particular to an understanding about what the logic of solution procedures is. Evidently, the scaffolds supported the learners in the demanding process to look behind the multi-representational solutions. We call this the scaffolding self-explanation effect which refers to the elicitation of high-quality self-explanations and the acquisition of deep understanding (cf. section 4.7).

Scaffolding self-explanation prompts increase incorrect self-explanations and thereby hinder the acquisition of procedural knowledge. Scaffolding self-explanation prompts increased the number of rationale-based self-explanations and principle-based self-explanations but also of incorrect self-explanations. Incorrect self-explanations had, in turn, a detrimental effect on the acquisition of procedural knowledge. We call this the *paradox self-explanation prompt effect* because the instructional support measure of scaffolding self-explanation prompts unexpectedly leads to incorrect self-explanations and hinders the acquisition of procedural knowledge. Contrary to our expectations, the scaffolding self-explanation prompts did not help to *avoid* incorrect self-explanations but evidently even *evoked* them. As a consequence, the acquisition of procedural knowledge was impaired.

The latter contradicts the findings of Chi (2000) who assumed that incorrect self-explanations are harmless. According to Chi, generating incorrect self-explanations might even create an opportunity for conflicts to occur which can lead to self-explaining episodes of trying to resolve it (Chi et al., 1989; cf. VanLehn, 1999: impasse-driven learning). In order to notice such conflicts, the learners must actively monitor what the text is saying and how it fits in their mental model (cf. de Leeuw & Chi, 2003). The crucial aspect in this respect may be, however, that the learners need enough free cognitive capacity to resolve their misconceptions or impasses. Evidently, this was not the case for our learners in the conditions with scaffolding self-explanation prompts. Even when learning with worked-out examples, they experienced a high amount of cognitive load – much higher than their counterparts in the conditions without self-explanation prompts. First, this may be explained by the fact that very complex learning materials were presented: textual problem formulation, pictorially presented tree-diagrams, and / or arithmetical equations, and – in the case with scaffolding self-explanation prompts – the textual information included in the scaffolds. Secondly, the scaffolding self-explanation prompts evidently directed the attention on conceptual knowledge which was at the cost of procedural knowledge. Thus, findings of this Experiment 2 show heterogeneity of learning outcomes: the two outcome measures were not homogeneously influenced by the scaffolding self-explanation prompts. This might be due to the highly complex learning environment. Evidently, the learners reached their upper limit of their working capacity by focusing conceptual knowledge so that correct essential processing with respect to procedural knowledge was hindered (Mayer & Moreno, 2003).

The present results and the results by Große and Renkl (in press) as well as by Schworm and Renkl (2006b) suggest that in complex example-based learning environments (e.g., examples with multiple solution methods or with right or wrong solutions) instructional support procedures (e.g., self-explanation prompts or demands to look for errors) do not necessarily enhance general active processing but direct the attentional focus on specific aspects. The effect specifity of instructional procedures such as self-explanation prompts are probably due to the fact that mentally representing the complex, multi-representational learning contents induce high working memory load just for the representation of the contents (*intrinsic load*; Sweller, 2005). This is probably especially true for learners with less favorable learning prerequisites (cf. General Discussion, section 6.1.1). For these learners, the intrinsic load may be overwhelmingly high. They have to hold all the elements of the complex learning material and their interrelations simultaneously in working memory – particularly because they cannot “chunk” information effectively. Thus, the complex learning material *and* the less favorable learning prerequisites of the learners can cause a high intrinsic load.

In addition, there are very high demands of essential (Mayer & Moreno, 2003), learning-related processing (germane load) when each representation and their interrelations should be understood. Further enhancement of essential processing (germane load) by instructional support procedures is hardly possible due to working memory limitations. Therefore, instructional procedures do not have profound general effects on active processing and learning outcomes, but direct the attentional focus on specific aspects. The instructional interventions of this Experiment 2 might have just supported the processing of specific aspects but they did not lead to generally more active processing and generally better learning outcomes. Therefore, the effects of our instructional interventions that were primarily intended to maximize the profit of learning from multiple representations were presumably confined to conceptual knowledge (for a comparison of the findings of Experiment 1 and 2 see General Discussion, section 6.1).

Another issue worth to be considered is that instructional procedures may indirectly communicate to the learners what is important. In addition, we conjecture that subjective learning goals play an important role in determining what the learners focus on and thereby influence what is learnt (see also Gerjets & Scheiter, 2003; Schnotz, 2005). Probably, the scaffolding self-explanation prompts indirectly communicated to concentrate on conceptual knowledge – inducing a subjective learning goal of conceptual knowledge. Consequently, the learners directed their attention in the scaffolding self-explanation conditions to the rationale of the solutions (understanding-why) which was at the costs of acquiring procedural knowledge. Especially, the principle of cognitive economy formulated by Schnotz in his theory on multimedia learning from text and pictures implies that learners have goals that determine what they process: They try to invest just as much cognitive processing as it is necessary to reach the subjective learning goals.

With respect to learning conceptual knowledge *and* procedural knowledge, it is not functional to assume that learners can “learn all at once” – at least for the participants of this Experiment 2 (cf. section 6.1). As a remedy, sequences of phases could be implemented that are devoted to conceptual knowledge as well as procedural knowledge. Such sequences should help to avoid dysfunctional concentration on certain aspects at the expense of other important learning goals. Mayer and Moreno (2003) recommend such an off-loading when learners are overloaded with essential processing demands.

In sum, we plea for a realistic stance on learning with multi-representational examples. They offer unique possibilities of fostering understanding. However, for enhancing knowledge (i.e., procedural knowledge) which can also be acquired by processing one representation, it might be more parsimonious to provide the learners with only one representation. Thus, we agree with Ainsworth (in press): “... it seems wise to use the minimum number of representations” (p. 12). When implementing instructional support procedures such as scaffolding self-explanation prompts, it has to be considered that they implicitly guide the learners’ attention on specific aspects of the learning materials which might have trade-offs with respect to other aspects. If multiple learning goals are to be addressed, a sequencing strategy might be a remedy with this respect – especially if the learners have less favorable learning prerequisites. However, this assumption has to be tested in further experiments.

5.7.2 Practical Implications

The most direct practical implication of this study is that learning environments that use multiple representations should include an integration help and scaffolding self-explanation prompts to enhance deep-level understanding. In addition, our results show that scaffolding self-explanations can lead to incorrect self-explanations which can hamper procedural knowledge. This suggests that incorrect self-explanations are not in any case as harmless as argued by Chi (2000) but can severely impede learning. In this context, it is important to note that the participants of this experimental research were school students, and our finding confirms the assumption of many school teachers – as we have heard in many further education course with (German) teachers – that a danger of self-explanations in contrast to instructional explanations are incorrect self-explanations which lead to incorrect knowledge. Thus, in the teaching of mathematics and in further research, it should be carefully analyzed how these incorrect self-explanations can be corrected.

5.7.3 Limitations and Future Directions

How far can the present findings be generalized? We have shown the use of multiple representations embedded in worked-out examples and of two instructional support procedures (integration help and scaffolding self-explanation prompts) in the context of one knowledge domain (i.e., complex events / probability theory). Thus, our research was embedded in mathematics, a well-structure learning domain. As self-explanations in general (i.e., not specifically related to the integration of different representations) have proved 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 different learning contents. However, an empirical test of this assumption is necessary in future studies. In addition, the effects of multiple representations and an integration help need to be examined in future research in the context of other domains.

A limitation that has to be acknowledged is that in this study only one type of learners (i.e., students of German gymnasiums, highest track of the German three track system) was included. More research is needed to include other populations, such as younger students or lower-achieving students.

Furthermore, in future studies, learning environments with multiple representations should be analyzed that include different types of scaffolding self-explanation prompts for learners at different levels of skill acquisition (cf. Conati & VanLehn, 2000). Moreover, self-explanations could be diagnosed online in order to provide an immediate and dynamic adaptation of scaffolding procedures (e.g., Aleven et al., 2001).

An open question with respect to the scaffolding self-explanation prompts refers to long-term effects. We suggest that scaffolding self-explanation prompts are especially helpful at early learning stages while as learners become more proficient in the specific topics even simpler forms of prompting can successfully trigger self-explanation (cf. Conati & VanLehn, 2000).

As mentioned above sequences of learning phases should be implemented that are devoted to – at least – conceptual knowledge as well as procedural knowledge. It should be experimentally tested if such sequences help to foster both conceptual knowledge and procedural knowledge.

6. General Discussion

This last chapter concludes with an overall discussion of the results of this research. Furthermore, the theoretical and practical implications of this dissertation are discussed. Afterwards, limitations of this research are critically addressed. Based upon this discussion fruitful lines of future research are pointed out. Finally, a closing in is presented.

6.1 Discussion of Results

The overarching goal of this dissertation was to empirically test the effects of multiple representations embedded in worked-out examples and the instructional support procedures of an integration help and self-explanation prompts.

In summary, this dissertation made four essential contributions to research on learning from worked-out examples. (a) Multiple representations embedded in worked-out examples and an integration help foster conceptual knowledge (additive effect). With respect to procedural knowledge, it is equally effective to provide multi- or mono-representational solutions or presenting the multi-representational solutions with or without an integration help (Experiment 2). (b) Self-explanation prompts – scaffolding (Experiment 1 and Experiment 2) and open (Experiment 1) – foster principle-based self-explanations and rationale-based self-explanations (Experiment 1 and Experiment 2) as well as procedural (Experiment 1) and conceptual knowledge (Experiment 1 and Experiment 2). With respect to rationale-based self-explanations and conceptual knowledge, scaffolding self-explanation prompts are especially effective when compared to open prompts (Experiment 1). Particularly, scaffolding self-explanations support the integration of multiple representations, as indicated by the understanding of the multiplication rule (Experiment 1). (c) Moreover, scaffolding self-explanation prompts foster conceptual knowledge *by* the elicitation of rationale-based self-explanations (Experiment 1 and Experiment 2). (d) Scaffolding self-explanation prompts foster principle-based self-explanations (Experiment 1 and Experiment 2) and *thereby* enhance procedural knowledge (Experiment 1) or conceptual knowledge (Experiment 2). Though, scaffolding self-explanation prompts also elicit incorrect self-explanations; the latter can hinder the acquisition of procedural knowledge (Experiment 2).

6.1.1 Differentiated Effect of Scaffolding Self-Explanation Prompts on Procedural Knowledge

In Experiment 1 and Experiment 2 – in which very similar learning materials and test materials were implemented – heterogeneous results of scaffolding self-explanation prompts on procedural knowledge, incorrect self-explanations, and mediation effects emerged. With respect to procedural knowledge, in Experiment 1, a positive effect of scaffolding self-explanation prompts was obtained. In Experiment 2, a negative effect emerged. Moreover, though in both experiments, scaffolding self-explanation prompts fostered principle-based self-explanations, in Experiment 1, principle-based self-explanations mediated the effects on *procedural* knowledge whereas in Experiment 2 principle-based self-explanations (besides rationale-based self-explanations) were the crucial mediator with respect to *conceptual* knowledge. Furthermore, in Experiment 2, scaffolding self-explanation prompts elicited incorrect self-explanations that hindered the acquisition of procedural knowledge (paradox self-explanation prompt effect, cf. section 5.7.1). Thus, contrary to our expectations, in Experiment 2 the scaffolding self-explanation prompts did not help to *avoid* incorrect self-explanations but evidently even *evoked* them. Presumably, the effect of prompts on procedural knowledge depends on the prior knowledge level of the learners.

Apparently, attending to *both* knowledge types imposes high demands on essential, learning-related processing (cf. Mayer & Moreno, 2003). Learners who have less favorable prior knowledge and who therefore cannot “cluster” information effectively may reach their upper limit of their working capacity (Mayer, 2005a; Sweller, 2005) so that the necessary essential processing does not occur.

Against this background, it is important to note that the major difference between the two experiments was related to the type of learner: psychology students in Experiment 1 and gymnasiums students aged about 16 years in Experiment 2. Psychology students presumably have the better learning prerequisites as they have received more mathematics and statistics instruction in their life, and they are – in comparison to the school student population – a selected population with a positive bias: German psychology programmes are so-called *numerus clausus* programmes in which admission is primarily dependent on very good grades in school (gymnasiums). Their better learning prerequisites enabled the psychology students to attend to procedural aspects even when they were directed by the scaffolding self-explanation prompts to conceptual knowledge. For the gymnasiums students with their less favorable prerequisites the direction of attention by the scaffolding self-explanation prompts on conceptual knowledge prevented a correct processing related to procedural knowledge. Evidently, the effect of scaffolding self-explanation prompts on procedural knowledge is dependent on the learning prerequisites of the learners.

The assumption of the better learning prerequisites of the psychology students is confirmed by the following finding: In Experiment 1 and Experiment 2, two pretest problems were roughly comparable (the problem formulations have been simplified a bit for the gymnasiums students). Actually, the psychology students had higher solution rates for these two problems as compared to the gymnasiums students: M = .56 (SD = .50) versus M = .40 (SD = .49); M = .53 (SD = .50) versus M = .43 (SD = .50). Thus, this supports the assumption of better learning prerequisites of the psychology students.

Their better learning prerequisites enabled the psychology students to attend to both procedural and conceptual aspects. Consequently, their self-explanations were not only related to conceptual knowledge but also to procedural knowledge and thereby also fostered procedural knowledge (mediation of principle-based self-explanations on procedural knowledge). Contrary, for the gymnasiums students with their less favorable prerequisites, it was only possible to attend to one knowledge type. Evidently, the scaffolding self-explanation prompts directed the attention of these learners exclusively on conceptual knowledge and simultaneously prevented a correct processing related to procedural knowledge. This assumption is confirmed by the finding that the self-explanations of the gymnasiums students were only related to conceptual knowledge (rationale-based self-explanations *and* principle-based self-explanations mediated the effects on conceptual knowledge). Moreover, in the gymnasiums sample the scaffolding self-explanations also elicited incorrect self-explanations and thereby hindered the acquisition of procedural knowledge (paradox self-explanation prompt effect) – indicating that these learners reached their upper limit of their working capacity by focusing conceptual knowledge. This interpretation is confirmed by the significantly higher cognitive load scores when the learners were provided with scaffolding self-explanation prompts.

In a nutshell, these across-experiment comparisons reveal that by employing very similar learning and testing materials across experiments with different samples, the possibility arises to detect differentiated effects on research participants with different learning prerequisites (see also section 6.2.1). It is particularly important that researchers on learning and instruction go into the schools to gain their participants and do not only recruit psychology students who evidently have better learning prerequisites. In sum, if researchers would like to generalize their findings on learning and teaching in school, school students should be included as research participants.

This may sound rather trivial. Nevertheless, in many studies on learning and instruction, the nature of the research participants is chosen rather incidentally. For instance, while several studies involve school-age children as participants (e.g., Moreno & Mayer, 1999; Tarmizi &

Sweller, 1988), a number rely instead on college-age students (e.g., Atkinson, 2002), or university students, especially psychology students. However, it would be helpful to determine whether the results of the reported studies generalize across learners of different ages and different cognitive learning prerequisites. Nevertheless, evidently, in research on learning with multiple representations, there is a lack of systematic comparisons of research participants of different age and learning prerequisites (cf. section 6.4.2).

6.1.2 Stable Effect of Scaffolding Self-Explanation Prompts on Conceptual Knowledge

Contrary to the effects on procedural knowledge, the results with respect to conceptual knowledge in Experiment 1 (psychology students) and Experiment 2 (gymnasiums students) fully corresponded to the theoretical assumptions. Multiple representations (Experiment 2), an integration help (Experiment 2), and scaffolding self-explanation prompts (Experiment 1 and Experiment 2) all have positive effects on this knowledge types. The latter effect is mediated by rationale-based self-explanations (Experiment 1 and Experiment 2).

The replication of the effect of the scaffolding self-explanation prompts on rationale-based self-explanations and thereby also on conceptual knowledge for both the gymnasiums students and the psychology students strengthens the robustness of these findings and demonstrates that the instructional support measure of scaffolding self-explanation prompts indeed proves to be a suitable method to overcome the difficulties of learners with a different background when learning with multi-representational examples (scaffolding self-explanation effect, cf. section 4.7 and 5.7.1). Furthermore, this finding suggests that learning outcomes which especially benefit from the integration of multiple representations (i.e., conceptual knowledge, cf. section 4.5.3) particularly profit from learning with multiple representations and corresponding instructional support procedures.

6.1.3 Additional Information in the Scaffolds

By providing only fill-in-the-blank self-explanations instead of complete instructional explanations and by fading out the scaffolds 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, as the scaffolding self-explanation prompts included additional information compared to the open self-explanation prompts, it might be that not the scaffolding-fading procedure itself but only the additional information in the scaffolds 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 and principle-based self-explanations) mediated the effect of scaffolding self-explanation prompts on conceptual knowledge. Second, there are meanwhile numerous findings that usual instructional explanations in worked-out examples are rather inefficient (e.g., Atkinson & Catrambone, 2000; Atkinson, Catrambone, et al., 2003; Gerjets, Scheiter, & Catrambone, 2003, in press; Hilbert et al., 2004; Renkl, 2002). Thus, it is not probable that the pure "reception" of the incomplete instructional explanation in the scaffolding 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-explanation in the second isomorphic example was 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 scaffolds in the first isomorphic examples 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 raise for comparing and contrasting this answer with one's own (cf. Roy & 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). Anyhow, these learning processes only occur if the learners actively self-explain a presented answer or, in our case, the information included in the scaffolds in some form (e.g., by filling in blanks and answering open self-explanation prompts). Thus, we assume that self-explaining is probably the crucial factor. However, an empirical test of the specific contribution of the additional information in scaffolding self-explanation prompts is necessary in future studies (cf. section 6.4.4).

6.2 Theoretical Implications

Based on the results of this dissertation, the following theoretical implications can be deviated.

6.2.1 Differentiated Effects of Instructional Measures on Conceptual and Procedural Knowledge

As already outlined, learning outcome measures on different knowledge types, that is, conceptual and procedural knowledge were included in this research. By including conceptual knowledge as a learning outcome variable, the shifted focus in mathematics teaching from learning only procedural knowledge to an emphasis on insightful understanding (cf. Ainsworth, 1997) was addressed.

With respect to procedural and conceptual knowledge, this dissertation revealed differentiated effects (see also section 6.1.1 and section 6.1.2) of the instructional support measure scaffolding self-explanation prompts. In Experiment 1, both types of self-explanation prompts (scaffolding and open) fostered procedural knowledge, whereas for enhancing conceptual knowledge scaffolding self-explanation prompts were particularly effective. In Experiment 2 – including learners with lower learning prerequisites as participants – enhancing conceptual knowledge was at the cost of procedural knowledge.

How to enhance conceptual and procedural knowledge is addressed quite often in research on learning and instruction (e.g., Rittle-Johnson, Siegler, & Alibali, 2001). For example, Rittle-Johnson et al. propose that conceptual and procedural knowledge develop in an iterative fashion and that improved problem representation is the crucial mechanism underlying the relations between them.

However, interestingly, in the literature on learning and instruction, it is rather unusual that such differentiated findings on conceptual and procedural knowledge are reported. This statement was confirmed by J. Sweller (personal communication, July 23, 2005). He also tried to obtain differentiated effects on procedural and conceptual knowledge in many studies but – according to his own statement – never succeeded. Relating the differentiated findings of this research to Sweller's cognitive load theory, it can be concluded that the effect specifity of instructional procedures such as self-explanation prompts are probably due to the fact that mentally representing the complex, multi-representational learning contents induce high working memory load just for the representation of the contents (intrinsic load; Sweller, 2005). In addition, there are very high demands of essential (Mayer & Moreno, 2003), learning-related processing (germane load) when each representation and their interrelation should be understood. Further enhancement of essential processing (germane load) by instructional procedures cannot have profound general effects on active processing and learning outcomes, but direct the attentional focus on specific aspects. Consequently, the learners concentrate intensively on these aspects but neglect other knowledge types. Thus, the iterative process with respect to conceptual and procedural knowledge proposed by Rittle-Johnson et al. (2001) can only work if the learners have sufficient cognitive capacity to process both knowledge types simultaneously.

In a nutshell, according to J. Sweller (personal communication, July 23, 2005) the differentiated findings on conceptual and procedural knowledge of this dissertation can supplement cognitive load theory by providing evidence for a specific essential processing which might be at the cost of essential processing of other aspects of the learning material.

Moreover, these findings highlight the importance of including different learning outcome measures in order to have the possibility to assess possible differentiated effects of a learning arrangement.

6.3 Practical Implications

In the following, practical implications of this research are derived.

6.3.1 Provide Multiple Representations and Enhance the Effects with Instructional Support Measures

First, this research provides us with a set of empirically based principles that can practically guide the design of learning environments employing multiple representations. *(a) Multiple representations.* The findings with respect to this aspect suggest the following instructional design guideline for multimedia learning environments involving mathematics: Provide multiple representations instead of single representations only when they seem to be necessary or especially helpful in reaching certain learning goals. Otherwise refrain from multiple representations. Moreover, the potential of learning with multiple representations can only be exploited when instructional support measures (i.e., integration help and scaffolding self-explanation prompts) are implemented (cf. Moreno & Durán, 2004). *(b) Integration help.* If an instructional designer intends to use multiple representations, there is the principle of integration help that should be kept in mind. If a classical integrated format cannot be realized, color-coding combined with a flashing procedure offer a promising possibility – if the integration of the multiple representations is needed for the learning goal (see above) and high visual-search conditions are presented (Atkinson, 2005). *(c) Scaffolding self-explanation prompts.* The findings with respect to scaffolding self-explanation prompts suggest the following instructional design guideline for learning with multiple representations: Scaffolding self-explanation prompts can strongly foster the integration and understanding of multiple representations (scaffolding self-explanation effect, cf. section 4.7 and section 5.7.1). However, the instructor has to carefully consider that instructional support procedures such as scaffolding self-explanation prompts implicitly guide the learners' attention on specific aspects of the learning materials which might be at the cost of other aspects (paradox self-explanation prompt effect, cf. section 5.7.1).

6.3.2 Example-Based Learning Does Not Only Foster Procedural Knowledge but Also a Deep Conceptual Understanding

A common misconception among teachers with respect to example-based learning is that example-based learning only fosters algorithmic knowledge (procedural knowledge), but not a deep conceptual understanding (cf. Renkl, Schworm, & Hilbert, 2004).

It is assumed that learners try to remember the worked-out solution steps of a few worked-out examples and then apply these solution steps on similar tasks. This misconception is closely related to the assumption of many people that example-based learning is a traditional, *nonconstructivist* learning method with too much emphasis on presenting contents instead of construction activities (cf. Renkl, 2005) – to say it shortly: to train the learners to solve future similar tasks without a deep understanding.

However, such a conception of example-based learning completely neglects the potential of this method. By self-explaining the principles which are applied in the solution steps and the rationale of the principle, the learners gain a deep conceptual understanding of the subdomain. This dissertation put an emphasis on conceptual understanding and was able to show that multi-representational examples – supported by an integration help and scaffolding self-explanation prompts – cannot only enhance procedural (Experiment 1) but also conceptual knowledge (Experiment 1 and Experiment 2). Thus, it can be recommended to teachers and instructors to implement worked-out examples not only to enhance procedural knowledge but also to foster conceptual knowledge.

6.4 Limitations and Guidelines for Future Research

A last question that is raised refers to the generalizability of the findings of this research. Possible restrictions with respect to generalizability are discussed. Based upon this discussion fruitful lines of future research are pointed out.

In this research, the use of multiple representations and two instructional support measures (an integration help and scaffolding self-explanation prompt) in the context of mathematics, a well-structured learning domain was analyzed.

6.4.1 The Domain

In this dissertation, the topic complex events of the subdomain probability theory was chosen as the learning content – addressing the critics of Atkinson (2005) that it is important to examine whether the findings on multiple representations can be generalized beyond geometry instruction to other subdomains of mathematics. Though it is a strength of this work, that a mathematical subdomain other than geometry was chosen, the question arises if the findings with respect to multiple representations, the integration help, and scaffolding self-explanation prompts can be generalized to similar well-structured domains such as physics and chemistry as well as also to ill-structured learning domains such as English (e.g., writing a poem) or arts (e.g., creating a sculpture). With respect to ill-structured learning domains, it is not possible to provide a manageable set of solution steps that directly lead to the final answer (Renkl, 2005). For these domains, an example provides just the problem and a solution (no steps); such examples are called *solved example problems*. Rummel and Spada (2005), for instance, provided video-based solved example problems of a successful computer-mediated collaboration in interdisciplinary problem solving on a psychiatric case which led to a better joint diagnosis than learning with a script. Taken together, the range of skill domains – including ill-structured domains – should be further broadened in research on multi-representational examples.

6.4.2 The Type of Learners

Though this dissertation has contrasted two types of learners (i.e., psychology students and gymnasiums students) – which is a benefit – more research is needed to determine how to incorporate other populations, such as younger students or lower-achieving students. As worked-out examples leave relatively many cognitive resources for gaining understanding, this approach should be especially appropriate for such populations. However, as the findings of this research indicated, learners with less optimal learning prerequisites than psychology students might have difficulties to focus on several aspects of the learning material (i.e., different knowledge types) at once. First, this finding suggests that in a series of experiments with participants of different age groups and different learning prerequisites, different levels of competence could be diagnosed, and it could be analyzed down to and up to which level of competence the learners still exploit the potential of learning with worked-out examples. Second, for learners with lower learning prerequisites, a remedy with respect to the cognitive overload might be to sequence the presentation of different aspects of the learning material so that, for example, in a first phase conceptual knowledge is focussed and after that, in a second phase, procedural knowledge. Such sequences should help to avoid dysfunctional concentration on certain aspects at the cost of other important learning goals. This should be addressed in future studies.

6.4.3 Evidence from Experimental Settings of Limited Ecological Validity

The two studies of this dissertation were conducted in well-controlled laboratory settings and within learning environments of a limited range with respect to both the content covered and the time span for the development of a complex skill. In order to test whether the findings of this dissertation hold true for real school settings, it would be fruitful to analyze the effects of (a) the implementation of the learning environment in a curriculum on complex events, (b) an extended learning environment that covers a broader topic (e.g., probability theory), and (c) in which the state-of-the-art of designing example-based learning is realized in a consequent way (e.g., including an integration help and scaffolding self-explanation prompts) and implemented in school lessons or university contexts (cf. Renkl, 2005).

6.4.4 Effect of the Additional Information in the Scaffolds

As mentioned in section 6.1.3, further studies should explore the specific contribution of the additional information in the scaffolding self-explanation prompts. Though it was found that the quality of self-explanations mediated the effect of scaffolding self-explanation prompts, an experimental study should compare the scaffolding condition with a condition providing the instructional explanations that were included in the scaffolds.

6.4.5 Subjective Learning Goals of the Learners

Against the background of the findings of Experiment 2, it can be concluded, that learners seem to cope with the complexity of the learning demands by focusing attention on specific aspects of the learning materials. It can be conjectured that the focus is influenced by the subjective goals of the learners. Especially, the principle of cognitive economy formulated by Schnotz (2005) in his theory on multimedia learning from text and pictures implies that learners have goals that determine what they process: They try to invest as much cognitive processing as it is necessary to reach the subjective learning goals. As instructional procedures indirectly communicate to the learners what is important, it can be assumed that the learners derive the learning goals from the learning material – internalising them as their subjective learning goals. Consequently, the learners focus on these aspects. This, in turn, enhances corresponding learning outcomes (cf. Schnotz). In this research, the self-explanation prompts might have influenced the subjective learning goals of the participants. Though the subjective learning goals were not assessed in this research, the learning outcome data showed that without prompts, most learners concentrated on how problems are solved (as it is probably the case in most learning situations in schools). The latter indicates a subjective learning goal of procedural knowledge. Contrary, the prompts directed most learners' attention to the rationale of the solutions (conceptual knowledge). Against this background, in future research, the subjective goals have to be taken into account when analyzing the use of multiple representations and the resulting learning outcomes (for the relevance of subjective goals in example-based learning see also Gerjets & Scheiter, 2003).

6.4.6 Diagnosing the Incorrect Self-Explanations and Providing Adaptive Support

The incorrect self-explanations elicited by the scaffolding self-explanation prompts might not only be a deficit – as clearly indicated by this research (contrary to Chi, 2000).

Several prominent models of cognitive skill acquisition such as VanLehn’s Cascade (e.g., 1999) emphasize that errors are triggers for reflection that deepen understanding. Additionally, many classroom teachers emphasize that effective instruction should take up errors as opportunities for in-depth discussions in order to deepen understanding (Renkl, 2005). Though this research suggests that learners were cognitively overwhelmed to engage in reflection, by providing adequate support measures combined with sufficient time, the deficit of incorrect self-explanations might become a chance for revising own misconceptions. Clearly, there needs to be significantly more research conducted on this topic in the future.

6.5 In Closing

The findings of the two experiments in this dissertation revealed four important implications for instruction and research on multi-representational examples:

(a) Exploit the full potential of multiple representations by instructional support measures on integration and understanding. Including instructional support measures such as an integration help and scaffolding self-explanation prompts on integration and understanding in multi-representational learning environments is more effective than pure multi-representational learning arrangements without such support (cf. Moreno & Durán, 2004). These results substantiate the need to provide support to the learners so that they can exploit the full potential of learning with multiple representations.

(b) Scaffolding self-explanation effect and paradox self-explanation prompt effect. Scaffolding self-explanation prompts elicit high-quality self-explanations that are slightly out of reach for learners without this assistance and foster deep conceptual understanding. In this dissertation it is proposed to call this the scaffolding self-explanation effect. The case of the scaffolding self-explanation effect is a very good instance to support the notion that effective

learning needs a well-balanced mixture of provided structure and information (e.g., scaffolds) and room for active knowledge construction (e.g., self-explanations) (cf. Renkl, 2005).

However, the scaffolding self-explanation prompts also elicited incorrect self-explanations which had a detrimental effect on the acquisition of procedural knowledge. In this dissertation it is proposed to call this the paradox self-explanation prompt effect because an instructional support measure of scaffolding self-explanation prompts unexpectedly leads to incorrect self-explanations and hinders the acquisition of one knowledge type. The scaffolding self-explanation effect and the paradox self-explanation prompt effect are an innovation in research on self-explaining and supplement or respectively modify the work of Chi (e.g., Roy & Chi, 2005) and Renkl (2005) (cf. section 4.7 and section 5.7.1).

(c) Differentiated effects on different learning outcomes. Although in this research a learning approach that reduces demands on the learner was implemented – example-based learning is a load-saving approach because the learners are released from finding a solution on their own – only one (i.e., conceptual knowledge) of the two knowledge types in the learning outcome measures was consistently increased in both experiments. Evidently, not all knowledge types can be equally effectively enhanced by multi-representational examples: Only learning outcomes that especially benefit from the integration of multiple representations (i.e., conceptual knowledge) particularly profit from multiple representations. Interestingly, the Experiment 2 of this dissertation is one of the first studies to show differential effects on the acquisition of conceptual and procedural knowledge.

(d) Different learning outcomes of different types of learners. Learners with better learning prerequisites are able to focus different knowledge types whereas learners with less favorable learning prerequisites deal with the complexity of the learning environment by focusing on certain aspects which is at the cost of other knowledge types. These findings underscore that it is essential to systematically vary different types of learners in research on learning and instruction.

I hope that this research will contribute to a better understanding of learning with multi-representational examples and corresponding instructional support measures. In addition, I hope that it will stimulate further investigations in this rapidly expanding area of research that has such important implications for future educational practice.

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