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Computer-Based Visualizing:

Learning from Science Texts by Means of Self-Generated Computer-Based Drawings

Dissertation zur Erlangung des Grades Dr. phil.
vorgelegt von
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1 Theoretical Background

1.1 Introduction

The structure of neurons and their action on other neurons is an example of content commonly learned in a biology class. Learning about these neurons is difficult without a picture that shows a neuron's structure and how it releases a neurotransmitter that binds to chemical receptors. In an informal survey of people around the age of 30, I found that they unanimously said that it was and is difficult to read a scientific text in a biology or chemistry or in another science class at school, and they can remember that usually there were and are depictions in the science books showing what is explained in the text.

Bau einer Nervenzelle

Wenn man gegen einen Ball tritt, verkürzen sich unter anderem Muskeln des Oberschenkels und Fußes. Dazu werden Signale von Nervenzellen oder Neuronen des Gehirns an bestimmte Nervenzellen des Rückenmarks , die alpha-Motoneurone, übermittelt. Die alpha-Motoneurone verarbeiten die Signale. Sie senden ihrerseits über Fortsätze Meldungen an die betreffenden Skelettmuskeln und veranlassen so deren Kontraktion.
Für Aufnahme von Signalen besitzt ein Alpha-Motoneuron besondere Strukturen (siehe Abbildung 253.1). Dazu zählen vom Zellkörper ausgehende, meist stark verästelte Fortsätze, die Dendriten. Am Zellkörper entspringt außerdem ein Axon, ein Fortsatz, der Signale weiterleitet und an seinem Ende an Muskelfasern übermittelt. Es kann beim Menschen z.B. vom Rückenmark zum Fuß ziehen und damit über 1 m lang sein. Zwischen dem Axon des Alpha-Motoneurons und den Muskelfasern sind Berührungsstellen ausgebildet. Dort werden Signale weitergegeben. Man bezeichnet diese Strukturen als Synapsen. Auch zwischen Nervenzellen gibt es Synapsen. Solche zwischen einem Alpha-Motoneuron und von Muskelfasern nennt man auch neuromuskuläre Synapsen.
Die Axone der Alpha-Motoneurone sind von einer Hülle umgeben. Sie wird von vielen hintereinander liegenden SCHWANN'schen Zellen gebildet. Diese enthalten die Substanz Myelin und wickeln sich mehrmals um die Axone. So entsteht eine Hülle von lamellenartigem Aufbau, die SCHWANN'sche Scheide oder Myelinscheide. Die SCHWANN'schen Zellen gehören zu den Gliazellen. Zu den Funktionen der verschiedenen Gliazellen gehören z.B. die elektrische Isolierung der Axone und die Steuerung des Axon-Wachstums. An den Stellen, wo zwei SCHWANN'sche Zellen zusammentreffen, liegt die Axonmembran über eine kurze Strecke frei. Diese freien Abschnitte tragen nach ihrem Entdecker die Bezeichnung RANVIER'sche Schnürringe, weil sie im Lichtmikroskop als Einschnürungen der Myelinscheide erkennbar sind.
Neurone des Zentralnervensystems bestitzen ebenfalls Dendriten und ein Axon. Ihre äußere Form ist variabel. So haben manche Neurone zahlreiche, stark verzweigte Dendriten, andere nur wenige, kaum verästelte. Viele haben ein Axon, welches oft nur wenige Millimeter lang ist, bei manchen ist es verzweigt. Auch Neurone des Zentralennervensystems sind von einer Myelinscheide umgeben, sie wird jedoch nicht durch SCHWANN'sche Zellen, sondern von anderen Gliazellen gebildet. Ein einzelnes Neuron des Zentralennervensystems verfügt durchschnittlich über etwa 1000 Synapsen.

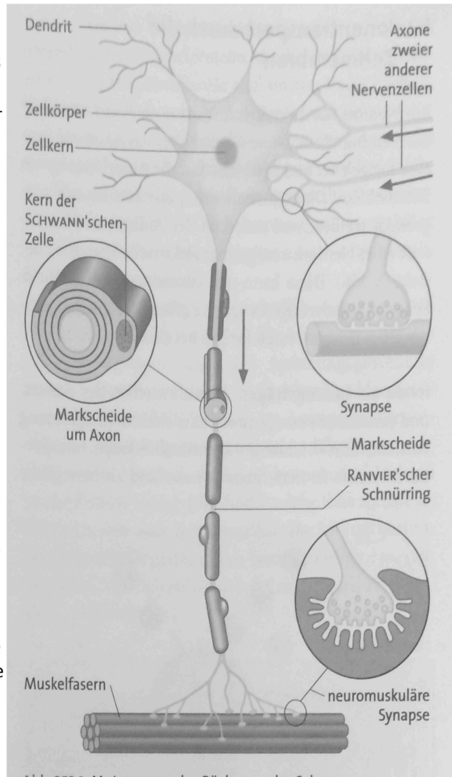

Abb. 253.1 Motoneuron des Rückenmarks, Schema.
Die roten Pfeile zeigen die Richtung des Erregungsflusses an.

Figure 1.1 Example of a learning text concerning the structure of neurons and their action on other neurons and a referring depiction in a science book (Bayrhuber, Hauber, & Kull, 2010, p. 253).

Learning with text and picture has been studied extensively in research concerning multimedia learning (Mayer, 2001, 2005). Multimedia refers to presenting material in both pictorial and verbal forms (Mayer, 2001, p. 5) and is a way to facilitate learning, especially with scientific content. One learning strategy that can help students to learn from science texts is the generative drawing strategy (van Meter & Garner, 2005): asking students to generate drawings as they read text. Figure 1.2 shows a drawing result of a student who was ask to draw a picture while reading and learning from a science text concerning the structure of neurons and their action on other neurons (see Figure 1.1).

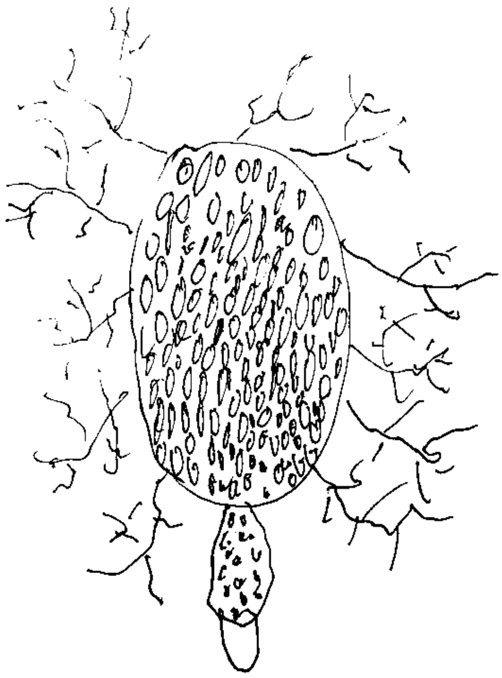

Figure 1.2 Figure showing a drawing that resulted from a students' attempt to comprehend the complex science text on the structure of neurons and their action on other neurons and to translate it into a picture (see Figure 1.1).

Studies concerning this drawing strategy showed that it is effective in enhancing students' learning from text (for an overview see van Meter & Garner, 2005, and van Meter & Firetto, 2013). There has only been one study on the effectiveness of computer-based drawing (Schwamborn, Mayer, Thillmann, Leopold, & Leutner, 2010), and this did not show positive effects on science text comprehension. However, because computers have found their way into school lessons and working with them is supposed to increase student's motivation, it is important to investigate whether successful learning strategies – in that case the generative drawing strategy – are also successful when they are used in a computer-based way. Thus, research is necessary to investigate which medium, paper or computer, is better to learn with. This thesis is aimed at investigating whether using computer-based generative drawing has a positive impact in general on learning outcome concerning science texts. Additionally, in the second of two studies of this thesis, computer- and paper-based drawing are compared to explore which is more effective for learning from science texts. The results will also be discussed with regard to the assumptions of the *Cognitive Load Theory* (CLT; Chandler & Sweller, 1991).

Both paper-based and computer-based drawings can be called ‘visualizations’.
In this thesis, the underlying models and theories concerning generative drawing are first described. Then, factors that can impact the effect of generative drawing, such as cognitive load, are reviewed and the current state of research on generative drawing is summarized. Based on this background, the research questions are derived. Two empirical studies testing these research questions are then presented. Finally, results of the studies are discussed with regard to their empirical, theoretical and practical contributions as well as their limitations. Additionally, directions for future research are given.

1.2 Generative Drawing

Using generative drawing to learn from a text means that students are instructed to draw a picture during the reading process, concerning all relevant information described in the text. Learner-generated drawing or here most commonly called generative drawing is a learning strategy because it is target oriented; the process of drawing is a strategy to organize information and can therefore enhance learning (van Meter & Garner, 2005). A learning strategy is defined as a scheme of an action sequence to achieve a learning target (Klauer, 2000) and as procedural knowledge to achieve a learning goal (Lukesch, 2001). Accordingly, van Meter and Garner (2005) defined generative drawing as strategic, representative, and constructive. In the following, the term generative drawing strategy therefore will be used.

The theoretical framework of the generative drawing strategy is the *Generative Theory of Drawing Construction* (GTDC) originally proposed by van Meter and Garner (2005), and revised by van Meter and Firetto (2013) into the *Cognitive Model of Drawing Construction* (CMDC). The GTDC is based on Mayer’s *Generative Theory of Textbook Design* (Mayer, Steinhoff, Bower, & Mars, 1995; Mayer & Gallini, 1990), which has evolved into the *Cognitive Theory of Multimedia Learning* (CTML; Mayer, 2001, 2005, 2009). The CMDC has also integrated the *Integrated Model of Text and Picture Comprehension* (ITPC; Schnotz, 2005) as well as research on self-regulated learning (SRL) and learning strategies, especially Winne’s SRL model (Winne & Hadwin, 1998; Winne & Perry, 2000). Thus, to understand the basic ideas of the GTDC as well as the CMDC, a brief digression and explanation of several important aspects of SRL, especially Winne’s model of SRL, the CTML, the ITPC, and the *Cognitive Load Theory* (CLT, Chandler & Sweller, 1991) are given, before explaining the GTDC and the CMDC in more detail.

1.3 Self-Regulated Learning

Several models of self-regulated learning state that, within the process of self-regulated learning, learners are active in designing and regulating their own learning process. However, within self-regulated learning theory, there are many terms that are used synonymously. Weinert (1982), for example, describes learning in general as self-regulated. Hence, the learners can affect all essential decisions: if, what, when, how and where they learn. Additionally, most SRL models posit that the learners must autonomously select, organize and integrate all relevant information they need to learn (e.g., Boekaerts, 1997, 1999; Schiefele & Pekrun, 1996; Winne & Hadwin, 1998; Zimmermann, 2001; for overviews see Leopold, 2009; Niegemann et al., 2008). These learning processes involve cognitive, metacognitive, and motivational components (McCombs, 1989; Schiefele & Pekrun, 1996; Schraw, Crippen, & Hartley, 2006). To manage the learning processes, learners have to use learning strategies they know. According to Mandl and Friedrich (2006) learning strategies are behavior and thoughts are cognitions (cf. Weinstein & Mayer, 1986) that learners activate to affect and control their motivation and the process of learning. The Winne and Hadwin (1998) model is one example of a self-regulated learning model (for an overview of more models concerning self-regulated learning see Boekaerts, Pintrich, & Zeidner, 2000, and Zimmermann & Schunk, 2001) and plays a crucial role in the extension of van Meter's and Garner's (2005) Generative Theory of Drawing Construction into the Cognitive Model of Drawing Construction of van Meter and Firetto (2013) which will be explained in detail below.

Winne´s and Hadwin´s Model of Self-Regulated Learning

Concerning how learners control and regulate their learning, Winne (Winne & Hadwin, 1998; Winne & Perry, 2000) focuses on learners' metacognitive awareness and their control mechanisms. This means that after learners have filtered the demands of a task (phase 1: task perception stage) they set a corresponding goal (phase 2: goal setting and planning stage). This goal induces standards for performance, which correspond to several facets of the task. Thus, there can be multiple standards for a single goal once learners have selected different facets that they think are important for that task. After setting standards, the self-regulated learner applies cognitive operations (phase 3: acting stage), such as a learning strategy, to the learning material. When learners are metacognitively aware of which strategy matches best with specific conditions of a task, this can lead to selection of specific learning strategies during the planning phase. This ability reflects high quality self-regulation of the learners (Winne, 1995; Winne & Perry, 2000). Application of cognitive operations results in learning products. If the learning task is complex, multiple learning products are created while working toward the learning goal. By applying metacognitive self-monitoring, the learners are able to adapt their cognitive strategies. The learning products are compared to the standards the learners have filtered when setting the learning goal. If the learning products are in line with the standards the learners will stick to their plan and apply the cognitive operations. However, if the learning products are not in line with the performance standards, self-regulated learners will use metacognitive control to change their plan, select a new learning strategy, repeat parts of the already followed plan, or will adjust the performance standards (phase 4: adaption stage). Metacognitive awareness, metacognitive self-monitoring and metacognitive control build up a self-regulation cycle. All parts of the cycle will be repeated till the learning task is completed. Van Meter and Firetto (2013) use these self-regulation principles to extend the Generative Theory of Drawing Construction and to explain how drawing affects learning and how it can be used most effectively. This connection will be explained in the section about the Cognitive Model of Drawing Construction.

Learning strategies

Students need corresponding learning competence to be able to use self-regulated learning, namely to control and regulate the learning process and to accomplish the learning material. That requires a repertoire of learning strategies (e.g., Götz, 2006; Zimmermann, 1990). Mandl and Friedrich (2006), for example, differentiate five different categories of learning strategies: cognitive strategies, metacognitive strategies, motivational-emotional support strategies, cooperative learning strategies and resource-oriented strategies. Every category contains several concrete and executable learning strategies and will be shortly described in the following sections (for an overview see Niegemann et al., 2008, and Weinstein & Mayer, 1986). However, the major questionnaires concerning learning strategies, the MSLQ (Pintrich, Smith, Garcia, & McKeachie, 1993) and the LIST (Wild & Schiefele, 1994) differentiate only between three different categories, namely cognitive, metacognitive and resource-oriented strategies.

Cognitive learning strategies are strategies concerning information processing. This process consists of the actual information input, information processing and information storage (Wild, 2000). These learning strategies refer to learning and understanding information (McKeachie, Pintrich, Lin, & Smith, 1987) and can be subdivided into the following strategies: (a) rehearsal strategies, (b) organizational strategies and (c) elaboration strategies (cf., Weinstein & Mayer, 1986; Pintrich, 1989). Rehearsal strategies are used to repeat important segments of a given learning material. An example is repeated reciting.

Organizational strategies are used to restructure a given learning material by selecting the basic learning elements and creating links between them. Examples are the generation of tables or concept maps (Sumfleth, Neuroth, & Leutner, 2010). Elaboration strategies are used to activate prior knowledge to enable the understanding of the learning information and to make it possible for learners to store the information permanently in long-term memory (Mandl & Friedrich, 2006). Examples are taking notes, asking questions and imagery strategies. For the latter, learners create an image of what is to be learned. Images personalize the learning information for the students and make it easier for them to access the information. Additionally, these strategies can be further categorized into depth- and surface-oriented processing of the learning material according to the Levels-of-Processing Theory of Craik and Lockhart (1972), which describes memory recall as a function of the depth of mental processing, "…where greater depth implies a greater degree of semantic or cognitive analysis" (Craik & Lockhart, 1972, p. 675). Accordingly, organizational and elaboration strategies are categorized as depth-oriented processing, whereas rehearsal strategies are categorized as surface-oriented processing.

Metacognitive learning strategies are so-called 'superordinate strategies' (Schreiber, 1998; Weinstein & Mayer, 1986). While cognitive strategies are used to help learners to achieve a learning goal, metacognitive strategies are used to evaluate the learning process, i.e., planning, monitoring and regulating the learning process (e.g., Zimmerman, 2001):

Planning. At the beginning of a learning process, learners need to determine the learning objective. After that, learners determine how the learning process should look like and which learning strategies to use for reaching the learning goal. The learning goal is highly relevant because it is used at the end of the process to compare the goal with the learning outcome achieved.

Monitoring. This strategy is used to monitor one´s own learning progress according to the learning goal. Thereby the current state of the learning outcome is continuously compared to the target state of the learning outcome, i.e., the learning goal. Learners can, for example, ask themselves questions concerning the learning content to examine if they understand the information and try to draw their attention to the learning material (Niegemann et al., 2008).

Regulation. This strategy is the last stage in the chain of metacognitive strategies, in which learners evaluate whether they have reached their learning goal. If there are discrepancies between the outcome and the desired outcome, learners realize and acknowledge them. Acknowledgement of difficulties during the learning process is also important: Learners should use this information to avoid or eliminate these difficulties by adapting the learning processes in the future.

Motivational and emotional support strategies are linked with regulation strategies as they influence the learning process: If learners, for example, feel unable to reach a learning goal, and thus perceive lower self-efficacy, they might not invest much effort in carrying on with the learning process, i.e., in achieving the learning goal. This demonstrates that even if learners know sufficient cognitive and metacognitive strategies, they will not automatically use them. Especially in learning environments geared to independent and self-regulated learning, motivational aspects have a strong impact (Mandl & Friedrich, 2006).

Cooperative learning strategies refer, for example, to learning in groups or teams. Thus, these strategies are used in social contexts, like classes and seminars (and are also possible in some multimedia learning environments). However, to make cooperative learning strategies successful it is important to create adequate social learning situations. If these learning situations are created adequately they impact learners' learning motivation as well as learners' motivation to motivate others to learn. Academic help seeking, i.e., searching for help when learners are not able to make progress concerning their learning task by means of their own abilities and/or their prior knowledge, also belongs to the cooperative strategies. Concomitantly, academic help seeking is an important ability in self-regulated learning (Niegemann et al., 2008).

Resource-oriented strategies are also called support or secondary strategies (Wild, Hofer & Pekrun, 2006). They are used for optimization of the available resources. Examples are time management, designing and organizing the learning environment or focusing attention (Wild, 2000; Wild, Hofer, & Pekrun, 2006).

Generative Drawing as a Learning Strategy

According to the subdivision of the learning strategies shown above, the generative drawing strategy is a deep cognitive strategy with a metacognitive component (cf., van Meter & Garner, 2005). Schmeck (2010) proposed that learners who generate a drawing for a text need to generate an overall structure of the text instead of processing the given text information sequentially (which is the case when taking notes). Accordingly, Seufert, Zander and Brünken (2007) assumed that learners using the drawing strategy are forced to build up a coherent representation of the content. For that reason, Schmeck (2010) defined the drawing strategy as an organization and elaboration strategy, however, with a metacognitive component. When drawing while reading a text, the learner may experience difficulties when building up the mental model or the external drawing, and he or she may refer back to either the internal verbal representation or to the text to detect comprehension errors and to revise them. Thus, the drawing process might activate metacognitive strategies of monitoring and regulation.

Now that typical self-regulated learning models are introduced and the generative drawing is classified as a learning strategy, the Generative Theory of Drawing Construction and it´s revised version will be introduced. However, at first it is needed to introduce the *Cognitive Theory of Multimedia* Learning and the *Integrated Text and Picture Comprehension Model of Multimedia Learning* to get to know the theories on which the Cognitive Model of Drawing Construction is based on.

1.4 Cognitive Theory of Multimedia Learning

The Cognitive Theory of Multimedia Learning (CTML; Mayer, 2001, 2005, 2009) explains how learners process a combination of text and picture. This theory is based on three main assumptions: There are two separate channels (verbal and pictorial) for processing information (cf., Paivio, 1986); there is only limited capacity of the channels (cf., Baddeley, 1992; Baddeley & Hitch, 1974); and learning is an active process of selecting, organizing and integrating information. The theory acknowledges Paivio's Dual Coding Theory (1986) as well as Wittrock's Generative Learning Theory (1974, 1989). In line with these theories, Mayer assumes that learners who read a text with pictures build up an internal verbal representation of the text and an internal nonverbal (i.e., pictorial) representation of the pictures. The two representations are constructed separately and are integrated by generating referential connections to link the two different types of internal representations. According to Mayer (2001, 2005) three different cognitive processes are needed to build up the learner's integrated mental model of the to-be-learned content and to achieve a meaningful learning outcome (Mayer, Griffith, Jurkowitz, & Rothman, 2008), namely selection, organization, and integration. Within the process of selection students select relevant ideas, elements and relationships from the text and the pictures. On the basis of the selected elements, students then organize their internal representations to build a coherent representation of text and pictures. The last process is the process of integration, in which referential connections are generated between internal verbal and nonverbal representations. As mentioned before the learner's integrated mental model of the content is built and it is assumed to enhance the student's problem solving abilities and conceptual understanding (Mayer & Sims, 1994). On the basis of this theory and the cognitive processes of students' learning with text and pictures, van Meter and Garner (2005) built their Generative Theory of Drawing Construction which will be described in the next section. Additionally, a short digression will be provided whereby another theoretical concept concerning learning with text and picture is introduced:

The *Integrated Text and Picture Comprehension Model of Multimedia Learning.*

Integrated Text and Picture Comprehension Model of Multimedia Learning

The Integrated Text and Picture Comprehension model (ITPC) of multimedia learning was proposed by Schnotz, Seufert and Bannert (2002) and has several overlaps with Mayer´s CTML (2005, 2014). Both theories assume that cognitive processes of selection, organization and integration take place during learning with text and pictures.

Mayer (2001, 2005), however, distinguishes between words and pictures, whereby Schnotz (2002, 2005) distinguishes between descriptive and depictive representations. Based on the distinction of different sign systems introduced by Peirce (1906), namely the differentiation between symbols and icons, in the ITPC text is defined as a descriptive representation and pictures as depictive representations. Descriptive representations like words and sentences are examples of symbols, which "…have an arbitrary structure and are associated with the designated object by convention" (Schnotz, 2002, p. 102). Depictive representations like static or animated pictures are examples of icons and do not have an arbitrary structure. "Instead, they are associated with the designated object by similarity" (Schnotz, 2002, p. 103). Thus, texts are descriptive and pictures are depictive, however when the information is abstracted from the text and the visualizations to the student´s cognitive system, both external representations can be constructed into either descriptive or depictive representations (van Meter & Firetto, 2013). The ITPC describes the detailed process of integration of verbal and visual representations into a joint mental model.

According to the ITPC there are different levels of internal representations. The first level concerns the surface representation and is related to the external verbal or visual representation. In the process of text comprehension, the learner constructs a mental representation of the text surface structure by filtering the linguistic features of the text via verbal organization processes. Regarding the picture comprehension on this level the learner creates a visual image through perceptual processing based on the features of the graphic display (Schnotz, 2002). The second level is referred to as the propositional network. It includes the meaning of the provided text and picture and can be extended with prior knowledge. At this level in the process of text comprehension the text surface representation triggers conceptual organization processes, like semantic processing, resulting in a propositional representation (and a mental model). In the process of picture comprehension at this level the learner constructs a mental model (and a propositional representation) concerning the content shown in the picture. A propositional representation and a mental model can both be constructed from a text surface representation/descriptive representation, and from a visual image/depictive representation. Whereas the propositional representation is descriptive, the mental model is a structural analogue that is constructed by mapping structural features of the external visualization to knowledge in the long-term memory.

The described model is integrated into the revised GTDC by van Meter and Firetto (2013) which will be explained in detail later on in this thesis.

1.5 The Generative Theory of Drawing Construction

Van Meter and Garner (2005) transferred the cognitive processes described in the CTML to drawings generated while reading a text. In line with the assumptions of the CTML they assume that the adequate completion of all three cognitive processes is the prerequisite for successful learning, and that these three cognitive processes do not take place linearly. To understand the transfer of the main ideas of the CTML into the GTDC the following sections take a closer look at the three cognitive processes of selection, organizing, and integration during drawing:

Selection during Drawing

Students reading a text and drawing pictures that reflect the text content only have the text from which to select important elements, as no pictures are added to the text. This also means that students using generative drawing as a learning strategy can only select elements from the text to build their internal, non-verbal representation. When learning with multimedia (when both text and pictures are provided) both representations restrict the selection of elements from one another. Students reading a scientific text about a system, an event or a rule, like the example from the beginning, the structure of neurons and their action on other neurons, have to select the important elements from the text to understand the content. However, the selection of these elements "…guides the selection of corresponding elements from…" (van Meter & Garner, 2005, p. 317) the given pictures, thus students search for elements they have selected from the text. Looking at the picture in detail, in turn, would give learners the opportunity to find other important information and perhaps force them to select additional elements. Switching between looking at the text and the provided pictures, students' internal representations restrict one another by building up the mental model. Concerning learning from a text without provided pictures, but with help of generative drawing, they do not have such a restriction. Compared to multimedia learning, students who learn with text and self-generated drawing only have the text to select relevant content information. Thus, it seems to be all the more important that the learning text is well verbalized and that the instructions to build mental models are clear (cf., Hall, Bailey, &

Tillman, 1997; Levin & Mayer, 1993).

Organization during Drawing

The learning text (also called external verbal representation) is needed for selecting elements. The selected elements are in turn organized into a coherent internal verbal representation. The constructed internal verbal representation then guides the process of constructing the nonverbal representation. Referring to our neuron example in Figures 1.1, this means that the internal verbal representation determines how the axon and the dendrite (two elements selected from the learning text) should be organized in relation to one another within the nonverbal representation. However, it is important to say that this process is not necessarily linear and sometimes learners need to go back to the internal verbal representation or the text when generating a nonverbal representation (van Meter, 2001). An important benefit of the drawing process is that existing referential connections activate relevant images from prior knowledge. However, if students need to learn new concepts for which they do not have prior knowledge, they only have the learning text to generate a drawing, which serves as an external nonverbal representation. Van Meter and Garner (2005, p. 318) mention "…that learners' prior knowledge acts as a critical…support when using learner-generated drawing strategy."

Integration during Drawing

Following the GTDC there is no difference between the processes of organizing and integrating (contrary to the CTML). The internal verbal representation is needed to construct the internal nonverbal (i.e., pictorial) representation. In other words, to generate an external drawing, the integration of both the internal verbal and the internal nonverbal (i.e., pictorial) model is necessary. Hence, the drawing strategy forces the integration of the verbal and the pictorial model and is therefore thought to be more beneficial than learning with text and provided pictures.

Van Meter and Firetto (2013) highlight two shortcomings of the GTDC and developed a revised theory. However, they mention that their revised theory, called the Cognitive Model of Drawing Construction (CMDC) still includes the basic principles of the GTDC. The first shortcoming van Meter and Firetto (2013) point out is a limitation concerning the assumption of the two separate channels for processing the verbal and visual representations. Van Meter and Firetto (2013) believe into the two distinct channels but find that this perspective alone restricts thinking about the characteristics of knowledge representations and about the way the representations interact with each other. The second shortcoming refers to students' self-regulated learning system and the poor specification concerning the ways that drawing acts within this system.

1.6 The Cognitive Model of Drawing Construction

The Cognitive Model of Drawing Construction (CMDC, see Figure 1.3) developed by van Meter and Firetto (2013) is an extension of the GTDC (van Meter & Garner, 2005) and will be described in the following sections.

Integration of the ITPC into the CMDC

Van Meter and Firetto (2013) have adopted the central assumptions and the labels from the ITPC (Schnotz; 2002, 2005). Thus, following the ITPC they differentiate between descriptive and depictive representations. According to the CMDC, drawing begins when the learner forms a surface representation of linguistic characteristics filtered from the written learning text (or in some cases from spoken text). Through semantic processing of these characteristics, a propositional representation is constructed, containing structural elements and relations. Based on this propositional representation the learner creates a mental model, which van Meter and Firetto (2013), as in the ITPC, believe includes visuo-spatial information and is more determinate than the propositional representation (Gobert & Clement, 1999). The mental model is crucial for the learner to understand the components of a system (described in a text) and how, for example, different components work together and interact. The mental model, by analogy, represents structural relations in a system and is therefore, according to van Meter and Firetto (2013), the primary reason for generative drawing being an effective learning strategy. In Figure 1.3, illustrating the CMDC, the mental model is located on the right-hand side. At this level of the process the learner has nearly accomplished the goal of creating an external drawing. Now he has to translate the mental model into a perceptual/visual image. Finally, the learner can draw an external picture on the basis of the perceptual/visual image because this perceptual image converts the mental model into a form the learner can translate onto paper, by externalizing this depictive surface feature representation (van Meter & Firetto, 2013, p. 255). Additionally, it is important to say that not only the mental model influences the perceptual/visual image; the propositional representation and the surface representation of the text also do. However, van Meter and Firetto (2013) retain only one single arrow between the mental model and the perceptual/visual image (see Figure 1.3) in their depiction of the theory, to emphasize that the drawing strategy is most effective when the perceptual/visual image is developed from the mental model. In that case learners have already selected the important elements from the text, have organized them into a propositional representation, and have been forced to integrate the text and the depictive representation as well as to add their prior knowledge into the integration. Hence, it is assumed that when the perceptual/visual image is derived from the mental model, learners have processed the learning material deeply.

That prior knowledge is important for the learning strategy is already known from van Meter and Garner´s (2005) original Generative Theory of Drawing Construction. When learners do not have any provided pictures and only a text that provides information to draw a picture, they must consult their memory for prior knowledge concerning the content of the material and/or knowledge concerning described forms and shapes.

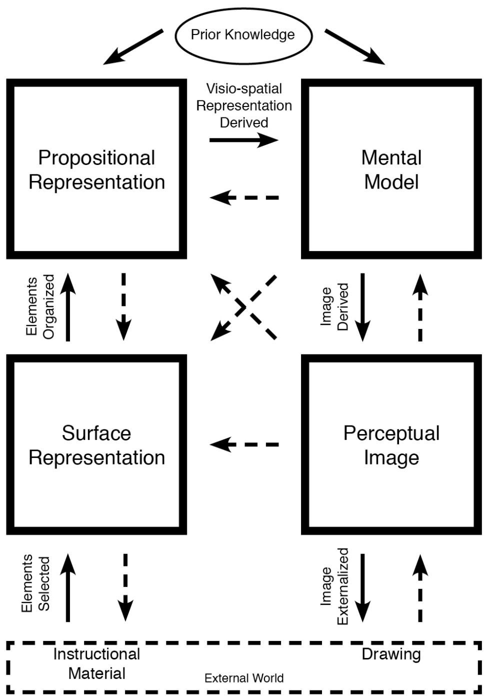

Figure 1.3 Graphic representation of the Cognitive Model of Drawing Construction according to van Meter and Firetto (2013).

Similar to the GTDC, the CMDC assumes that the drawing strategy influences learning from text positively by forcing the learner to integrate verbal and nonverbal representations. Additionally, the CMDC postulates that drawing supports construction of knowledge representations at each level as described in the ITPC. The integration of the ITPC into the CMDC reinforces the potential impact of the learning material on how to execute the drawing strategy. According to the CMDC the efficacy of the drawing strategy is influenced by different factors. If signalling, for example, is used in the learning text - such as printing important words in bold - it is easier for the learner to generate drawings. Additionally, a highly constrained text – i.e., a text consisting of a specific and detailed language such as the example of the structure of neurons in Figure 1.1- makes it easier for the learner to transfer a descriptive representation into a depictive representation. If the learning text is too detailed, however, the learner is able to translate descriptive symbols directly into a perceptual image without constructing a mental model before. Constructing a mental model, however, forces mentally organizing and integrating the to-be-learned information; in other words, it forces generative processing. Generative processing in turn is needed for deep-level understanding (Mayer, 2009), and thus it is thought to be the most important learning goal. Generating a mental model makes learners more able to recall main ideas from the learning material and apply new knowledge to novel problems (Azevedo, Cromley, & Seibert, 2004). According to Schnotz and Bannert (2003) differences in learners' external representations are also reflected in learners' mental models. Thus, in the CMDC it is emphasized that the effectiveness of the drawing strategy must be assessed with posttest assessments that are well-matched to the characteristics of learners' mental models and, therefore, also to the external representations learners generate during learning. Learners seem to have an advantage when posttests are consistent with the drawings they have learned with before (Schnotz & Bannert, 2003). For example, rather than asking learners to summarize all important terms and concepts of the learning text in a diagram, a better matched assessment would be to ask learners to complete missing parts of a provided visualization that they were asked to earlier create on their own.

To sum up, when using the drawing strategy it is important to take the mentioned aspects concerning the preparation of the learning material into account. Additionally, it is important to stick to some of the principles of multimedia design (Mayer, 2001, 2005, 2009) when creating learning material applying to the drawing strategy (see Chapter 1.6).

Integration of SRL into the CMDC

In contrast to the GTDC, the CMDC more strongly emphasizes the role of metacognitive processes during drawing, and, thus, models of SRL were integrated in the theory. Because drawing is not linear, according to van Meter and Firetto (2013) learners will always undergo recursions through the steps of the CMDC with iterative processes driving the learner back and forth between the internal and external representations. This was van Meter's and Firetto's motivation to incorporate self-regulation into the CMDC. Thus, they used dashed arrows in their graphic of the CMDC (Figure 1.3) to emphasise metacognition. These arrows show feedback cycles, which arise when learners try to draw and thereby realize that they have not well understood the content of the learning material. Mayer (2005, 2009) speaks of selection, organization and integration as cognitive processes, and Schnotz (2005), on the other hand, speaks of semantic processing. However, neither the CTML nor the ITPC explicitly explain how these cognitive and metacognitive processes work and do not speak of metacognitive processes. The GTDC implies how the process of drawing fosters metacognitive processes of monitoring and regulation. The CMDC, however, tries to explain how the process of drawing and metacognitive processes interact with other learning mechanisms (such as cognitive operations) by integrating three of the four phases of Winne's model of SRL. These three phases are (a) setting standards for performance, (b) applying (strategic) operations, and (c) monitoring goal progress (Winne & Perry, 2000). When learners are instructed to generate a drawing regarding a learning text, as self-regulated learners they will set standards, such as how many and which details they will include, how to represent the way structures fit together, and how accurate the drawing should be. Additionally, learners set standards referring to their learning outcome such as understanding of the described content and being able to remember specific relations and structures described in the text. Then, in the second phase students conduct cognitive operations to process and understand the learning material (i.e., the learning text) in order to reach the standards they have set. The cognitive operations lead to selection and organization of important elements from the text. Moreover, a specific cognitive operation concerning drawing is the translation of verbal descriptions into a visual depiction, that is, into a drawing. Finally, in the third phase of the self-regulation cycle of generative drawing, learners monitor where they are located on the way to their drawing and learning goal. Thereby, the learners check whether their drawing reaches the standards they have set before. If that is the case, they will continue the current drawing and the current learning process and so finish the learning task. However, if learners within this metacognitive process note that the goals regarding their drawing are not reached, they will go back to either their mental model or their propositional representation or even back to the learning text.

With regard to these three phases of SRL, the CMDC makes the following predictions: (1) Learners who know that it is important to generate accurate drawings will benefit more from this strategy than learners who do not know. (2) Learners' attention is directed during the process of drawing, namely towards descriptions in the learning text about how specific elements look and how they are related to one another. (3) Drawing triggers learners to use additional learning strategies, like self-questioning and the activation and integration of prior knowledge. Thus, using the strategy of generative drawing includes using other learning strategies, too. (4) Learners knowing when it is meaningful and promising to use the drawing strategy will be able and qualified to use the strategy when learning by themselves. Hence, it is (5) important to give learners sufficient instructions and support when they learn using this strategy, so that they know how to apply it correctly. Therefore, support should additionally instruct learners to generate accurate drawings including details.

To sum up, the CMDC (van Meter & Firetto, 2013) extends the prediction of the GTDC that learners, who apply the strategy of generative drawing correctly, automatically use self-monitoring more often by adding that if learners know how and in which situation to use the strategy, they are able to use this self-regulation learning strategy autonomously to reach their learning goal.

Besides cognitive processing (forced by the need to understand the learning material and to be able to generate a drawing that contains all relevant elements and their relations) as well as metacognitve processing (induced by the learners' realization of their deficiencies and increased self-monitoring; Ainsworth & Iacovides, 2005) the generative drawing strategy has an additional benefit: According to van Meter and Riley (1999) it is more difficult for learners to hide that they do not understand the learning material when they are asked to draw rather than to write. However, generating one's own drawings runs the risk of creating too much extraneous cognitive processing (or extraneous cognitive load; see the following section), leading to fewer cognitive resources being available for generative processing (Mayer, 2009).

1.7 The Cognitive Load Theory

Another important theory with regard to drawing is the *Cognitive Load Theory* (CLT) (Chandler & Sweller, 1991; Sweller, 1999, 2005, 2010; Sweller, van Merriënboer & Paas, 1998; for overviews see also Plass, Moreno, & Brünken, 2010; Sweller, Ayres, & Kalyuga, 2011). Although the CLT only refers to processes within working memory and not to the whole process of understanding, this theory is important to understand possible problems in the learning process by means of drawing.

Based on Baddeley's model of working memory (Baddeley, 1992; Baddeley & Hitch, 1974), CLT makes the assumption that the capacity of the working memory is limited (*Limited Capacity Assumption*). That is, the amount of new information that can be processed in working memory at the same time is limited. Additionally, working memory is also limited in duration when processing new information (e.g., Peterson & Peterson, 1959). Learners can only process 7 plus or minus two units at the same time, although they can use chunking as a strategy (Miller, 1956). However, more recent studies suggest that the capacity might be lower and that young adults only can process 3 - 5 chunks in their working memory (Cowan, 2010). By using chunking, learners organize or group input into familiar units or chunks (Miller, 1956) to expand the capacity of their working memory. However, the possibility to use chunking depends on the learner´s prior knowledge: Only with high prior knowledge are learners able to build up categories at a higher level, meaning that, if learners are not familiar with, e.g., the abbreviation for the American Psychological Association, they cannot treat APA as a single chunk. Concerning long-term memory, CLT assumes an unlimited capacity. During the process of learning with materials providing new information, the learner's working memory is strained. This cognitive workload is called cognitive load. The CLT differentiates between three different types of load, *intrinsic cognitive load*, *extraneous cognitive load* and *germane cognitive load* (Sweller et al., 1998).

Intrinsic Cognitive Load

Intrinsic cognitive load is a result of the learning task itself. It is the load caused by the complexity and the difficulty of the learning material, induced by element interactivity. Element interactivity refers to the number of units learners need to process simultaneously in working memory to make sense of and understand the whole learning material. An example is a science text like the one presented in Figure 1.1, which, on the one hand, contains different technical terms whose meanings are explained in the text, and the learner needs to learn them. Learning these words can be demanding because the learner can forget them, but this process will not impose a high load on working memory. According to Sweller (2010), "because the working memory load is light, the issue of 'understanding' does not arise" (p. 41) concerning learning the technical terms only. On the other hand, a science text describes relations and processes between technical components. Although these described processes may contain fewer relevant elements, the element interactivity can be high. The learners cannot consider only one of the elements – to understand the processes learners need to consider all elements simultaneously in working memory. If the element interactivity is high, the intrinsic cognitive load is high as well.

It is assumed that intrinsic cognitive load is fixed and cannot be changed by altering the material. Learning the elements as if they were isolated leads to learning but not to understanding, until all elements are processed in working memory (Sweller, 2010). However, according to Sweller (2010), instructing learners to learn high element interactivity material as if the elements are isolated and then learn the interactions later enhances learning compared to learning the interacting elements from the start. Another factor that impacts element interactivity and thus intrinsic cognitive load is the prior knowledge of the learner concerning the content (Gerjets, Scheiter, & Catrambone, 2004). Depending on the schemas a learner has already learned and built up in long-term memory, learning material that is complex and difficult for one individual can be simple for another. One schema might consist of different interacting elements; thus a supra-category has been built up as in chunking (as mentioned above). Accordingly, only that schema has to be processed in working memory, resulting in low intrinsic cognitive load. In sum it can be said that the more prior knowledge concerning a specific content a learner has, the less intrinsic load there is (Sweller, 2005). Correspondingly, Gerjets and Scheiter (2003) showed that a suitable difficulty of the learning task can optimize the intrinsic cognitive load, meaning that easy problems should be associated with low levels of intrinsic cognitive load whereas difficult problems should be associated with high levels of intrinsic cognitive load. However, whether a task is difficult or easy in turn depends on the learner's degree of expertise respectively on prior knowledge and should be adjusted according to this.

Extraneous Cognitive Load

Extraneous cognitive load is imposed by the manner in which information is presented to learners. This load describes the cognitive strain induced by the instructional design of the learning material. Excessive extraneous cognitive load can lead to *cognitive overload*, that is insufficient capacity in working memory, leaving no room for germane cognitive processes that would lead to successful learning. Originally, the CLT was developed to provide principles for the reduction of extraneous cognitive load (Sweller, 2010). For example, learning with text and pictures, like learning with an illustrated science book, whereby the illustration and the corresponding learning text are presented separately (e.g., on different pages), can lead to split attention (Ayres & Sweller, 2005). Thereby learners have to switch between these two presentations to collect all relevant information. This learning process leads to intensified cognitive strain which in turn leads to increased extraneous cognitive load and results in worse text comprehension. Thus, it is important that learning material is constructed in a way in which extraneous load is minimized (Sweller, 2005).

Germane Cognitive Load

Germane cognitive load is referred to as the load concerning learning and is devoted to constructing and automating schemas. Thus, it is the 'good' cognitive load. Germane cognitive processes are necessary to understand the learning material. If the learning material is designed in a way that reduces extraneous cognitive load, there is more capacity in the working memory for cognitive processes that induce germane cognitive load, thus leading to deeper learning.

Intrinsic, extraneous and germane cognitive load are additive (see Figure 1.4) and determine the total cognitive load (Sweller, 2010). If intrinsic and extraneous cognitive load together exceed the capacity of the working memory, there is not enough 'space' in working memory for germane cognitive load and thus for learning. To avoid this, learning material must be designed in a way that avoids extraneous cognitive load, especially in multimedia learning or learning with self-generated visualizations. These kinds of learning material have a high risk of evoking extraneous cognitive load (e.g., Leutner, Leopold, & Sumfleth, 2009; Mayer & Moreno, 2003; Sweller, 1999; van Merriënboer, 1997). However, generative drawing as well as multimedia learning (see the section about *Extraneous Cognitive Load*) could trigger cognitive overload in addition to fostering deep level understanding. The intensified activation of cognitive and metacognitive processes can, on the one hand, foster deeper understanding of the learning material but, on the other hand, it induces additional cognitive load. A possible cognitive overload is caused by the limited capacity of working memory and could decrease the learning outcome. Additionally, the drawing process itself can lead to a higher cognitive load caused by switching back and forth between text and drawing (Leutner et al., 2009) and/or by the drawing mechanisms itself.

Measurement of Cognitive Load

There are three basic kinds of empirical methods to measure cognitive load: using psychophysiological data, estimating performance, and gathering subjective data (Paas, Tuovinen, Tabbers, & van Gerven, 2003).

Psychophysiological techniques are used based on the assumption that physiological variables can reflect changes in cognitive functioning (Paas et al., 2003). These techniques include, for example, eye tracking (van Gog & Jarodzka, 2013) and measuring brain activity (Paas, Ayres, & Pachman, 2008).

Performance techniques can be subdivided into primary task measurement and secondary task performance (Paas et al., 2003). The first is based on task performance concerning the primary task, for example accuracy or error. The second is based on the performance of a secondary task that is performed concurrently with the primary task, like simple activities requiring sustained attention, such as detecting a visual or auditory signal (Paas et al., 2003). However, using secondary task performance can interfere with the primary task, especially if the primary task is complex (c.f. Brünken, Plass, & Leutner, 2003; Chandler & Sweller, 1996; Marcus, Cooper, & Sweller, 1996; Sweller, 1988).

Subjective techniques usually use questionnaires with one or multiple different scales on which learners state their experienced level of cognitive load. Subjective rating scale techniques are based on the assumption that people are able to introspect their cognitive processes and report them (Paas et al., 2003). Although subjective self-rating scales seem to be difficult and could also be criticized regarding assessing cognitive load (e.g., Brünken, Plass, & Leutner, 2003), Paas demonstrated for the first time in 1992 that people are able to state their perceived cognitive load. Many subjective techniques assess groups of associated variables (see Study II of this thesis; for an overview, see Nygren, 1991). However, unidimensional scales are also used to measure cognitive load (e.g., Paas & van Merriënboer, 1994; and Study I of this thesis), and seem to be valid and reliable measurements (Paas, van Merriënboer, & Adam, 1994).

Additionally, it is important to mention that cognitive load can be measured after the completion of a learning task (e.g., Kühl, Scheiter, Gerjets, & Edelmann, 2011; Leutner et al., 2009; Schwamborn, Thillmann, Opfermann, & Leutner, 2011) or online, meaning immediately and continuously after working with each section of a learning task (e.g., Opfermann, 2008; Paas & van Merriënboer, 1994).

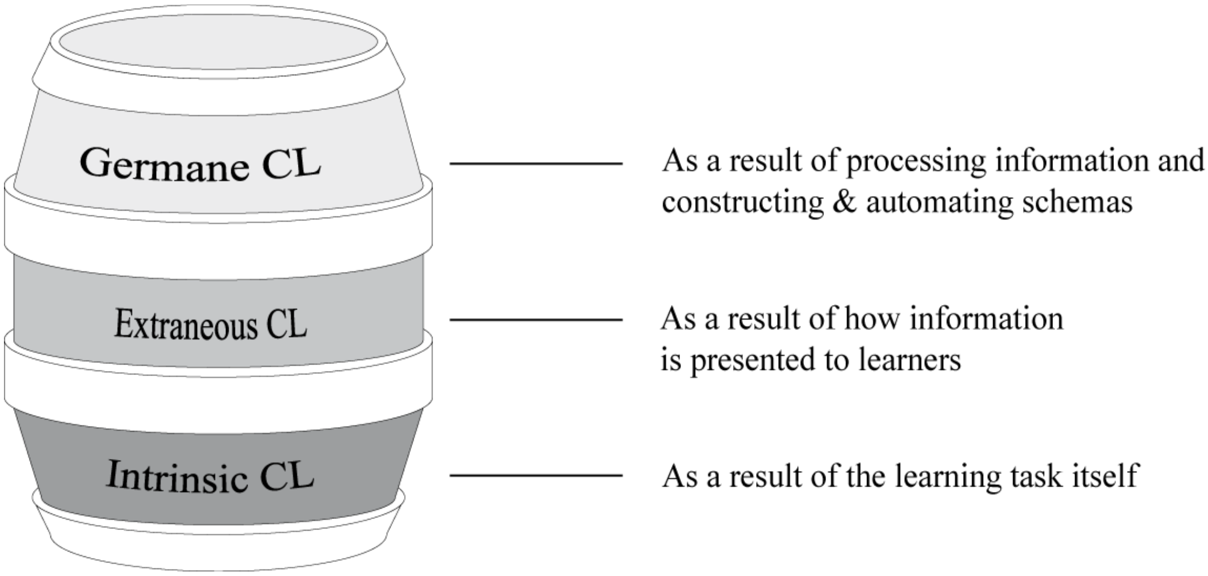

Figure 1.4 A visual representation of the total Cognitive Load (own illustration).

Some Principles of Multimedia Design

In the following, the principles of multimedia design that are relevant for learning with written text and instructor-provided pictures as well as for learning using the strategy of generative drawing, which is the focus of this thesis, are introduced. According to Mayer (2001, 2005, 2009) the *modality* and *redundancy principles* refer to learning from animations, respectively to narrations with instructor-provided pictures and will therefore not be explained here. The first principles described here are those that Mayer introduced to reduce extraneous processing. Then the principles intended for managing essential processing are explained.

Principles for Reducing Extraneous Processing (based on Mayer 2009, pp. 89-169):

(a) Coherence Principle: Learning is improved when interesting but irrelevant information (like words, pictures, symbols, sounds or music) are excluded from a multimedia presentation.

In this regard Garner and her colleagues introduced the term *seductive details* (Garner, Brown, Sanders, & Menke, 1992) which refers to interesting (i.e., learners perceive them as interesting and entertaining) but irrelevant material that is added to the presentation of the learning material (Mayer, 2009). Irrelevant information increases extraneous cognitive load because the learner uses cognitive capacity when trying to integrate the details. In the example of Figure 1.1, a seductive detail might be a necrotic neuron as a given pictorial element within a drawing toolbar showing also all relevant pictorial elements for generating a drawing (see Study I and II of this thesis). It might be an interesting element but is not relevant to understand the given information.

(b) Signaling Principle: People learn better when cues that highlight the organization of the essential material are added.

Signaling reduces extraneous cognitive load by guiding the learner's attention to important terms in the learning text. Thus, the learner's connection building is guided as well. Signaling can be used for verbal material, for example adding headings or pointer words such as "first…second…third" to the learning text, and also for the pictorial material, for example using arrows or distinctive colors (Mayer, 2009). In the example from Chapter 1 (see Figure 1.1), signaling could be done using pointer words, as in "First, the neuron releases a neurotransmitter, second the neurotransmitter binds to chemical receptors, third..." and using distinctive colors for relevant pictorial elements the learner needs for drawing.

(c) Contiguity Principle: Students learn better when corresponding words and pictures are presented near rather than far from each other with respect to time and space.

The spatial contiguity principle is realized when corresponding words and pictures are near each other on the page or computer screen, so that learners do not have to search and make use of their cognitive resources and are therefore able to hold words and corresponding pictures in working memory at the same time. The temporal contiguity principle is realized when corresponding words and pictures are presented at the same time, so that learners are more able to hold mental representations of both in their working memory at the same time. Hence, learners are more likely to be able to build up mental connections between verbal and visual representations (Mayer, 2009). Regarding learning material using generative drawing, an example of spatial contiguity can be that below the learning text on a screen or page corresponding drawing elements are presented, which students need to generate a drawing. An example of temporal contiguity is that the learning text is presented in portions simultaneously with corresponding relevant drawing elements and a corresponding partially pre-drawn drawing background (see Study I and II of this thesis), on which students can place their drawing.

Principles for Managing Essential Processing (based on Mayer 2009, pp. 171-199):

(a) Segmenting Principle: People learn better when a multimedia message is presented in user-paced segments rather than as a continuous unit.
When learning material is complex and learners are presented with fast-paced verbal and pictorial material, some learners will not fully understand one step in a process before the next one is presented. Thus, they may not have time to see the causal relation between one step and the next (Mayer, 2009).
Concerning learning material using generative drawing an example of an applied segmenting principle would be that only one paragraph about causal steps (e.g., about catching and having the flu, see Study I of this thesis) and its corresponding drawing elements as well as its corresponding drawing background is presented before the next paragraph. Additionally, this process is user-paced, meaning that the learners determine when they are able to work with the next paragraph.

1.8 State of Research on Generative Drawing

When summarizing the key statements of the theories described above, it is reasonable to assume that the learning strategy of drawing according to a learning text is effective concerning learning outcome. One reason is the double encoding of the learning material, which does not necessarily occur when students learn with text only (Paivio, 2006). A second reason is the building of the mental model which is said to be crucial for learners to understand the components of a system. Additionally, cognitive processes, like selection, organization and especially integration, are increasingly induced, as well as metacognitive processes such as monitoring.

However, research concerning drawing as a learning strategy has also been inconsistent. Positive effects of drawing as a learning strategy were shown, for example, by Alesandrini (1981), Lansing (1981), Leopold (2009), Leopold and Leutner (2012), Lesgold, Levin, Shimron, and Guttman (1975) (Experiment 2), Lesgold, DeGood, and Levin (1977), Schmeck (2010), Schwamborn, Mayer, et al. (2010), Schwamborn, Thillmann, Leopold, Sumfleth, and Leutner (2010), van Meter (2001), and van Meter, Aleksic, Schwartz, and Garner (2006). Overviews of several studies showing positive effects of the drawing strategy were given by van Meter and Garner (2005) and van Meter and Firetto (2013). However, studies by Leutner et al. (2009), Rasco, Tennyson, and Boutwell (1975), Snowman and Cunningham (1975), Schwamborn et al. (2011), Tirre, Manelis, and Leicht (1979) did not show benefits of the drawing strategy. For an overview see also van Meter and Garner (2005). At this point it is important to mention that the benefits of the drawing strategy so far have only been shown in studies in which reading and drawing were on paper (Leutner & Schmeck, 2014).

Support and Drawing

Looking at the research concerning generative drawing it is apparent that studies that found a benefit of using this strategy usually included some kind of support for students to generate a picture. In studies of Lesgold et al. (1975, 1977) students were supported by provided cut-out figures. An interesting finding in this study was that students only benefitted from the process of generating pictorial representations when the cut-out figures were accurate. When students had to choose between accurate and distracting figures, there was no positive effect of the support (Lesgold et al., 1975). Alesandrini (1981) showed that it is more effective (in terms of higher learning outcome) to let students draw about the content of a learning text dealing with electrochemical concepts than to let them write about it. Additionally, Alesandrini (1981) pointed out that it is important to support students during the drawing process by calling attention to specific parts of the text. The group that was instructed to work holistically, namely to attend to how system parts fit together, showed the strongest effects of the drawing strategy. Schmeck (2010) categorized these kinds of external support as *instructional support during the drawing process.* During the drawing process learners can be supported in choosing relevant elements to generate their pictures, in focusing on specific textual aspects, and in generating the drawing itself. According to van Meter and Firetto (2013), the study by Alesandrini (1981) used drawing support that served a *self-regulation function*. This form of support has a positive effect on the learner´s self regulation abilities. Concerning Alesandrini´s study (1981), the given instructions and support increase students' understanding of the drawing task, and as a result the learners are able to set specific drawing standards and appropriately direct their attention (van Meter & Firetto, 2013). Additionally, Ainsworth and Iacovides (2005) found that students who drew made four times as many self-monitoring statements than students who wrote.

In a recent study by Schwamborn, Mayer, et al. (2010), to which will be referred to in more detail later on, students were supported during the drawing process by a drawing prompt, which contained drawing elements in a toolbar at the top of each learning page and a partially pre-drawn drawing background. Besides a control group wherein the participants read the scientific learning text only, there were four drawing groups. One group drew, for each paragraph of the learning text, a picture concerning the important events in the paragraph. Another group underlined the most important information in the text, in addition to drawing. The third group was instructed to create a mental model before generating a drawing. Finally, the fourth group underlined the most important information in the text, created a mental model, and then drew. Students in all four drawing groups scored higher on transfer, retention and drawing posttests than the control group without drawing. However, there were no differences between these four groups, showing that the drawing prompt was enough support for learners to make the drawing strategy beneficial. According to van Meter and Firetto (2013) this form of support has a *constraint function.* Looking at the categorization of drawing support of Schmeck (2010) it is possible to classify this form of support into the category *instructional support during the drawing process.* It is a support to aid the drawing process itself.

In two studies of Schwamborn, Thillmann, and colleagues (2010) the same drawing prompt as in the studies of Schwamborn, Mayer, et al. (2010) was used as *instructional support during the drawing process*. In both studies a control group read a scientific learning text only. One drawing group was instructed to draw, for each paragraph, a picture concerning the important events in the paragraph. Another group got the learning text to read and additional provided pictures for every paragraph containing important content respectively coherences in the text. The last group had to draw their own pictures and got the provided ones after drawing to compare them. To control for learning time, Study 1 was conducted with fixed time and Study 2 with self-paced learning time. Results of Study 1 showed main effects of generative drawing on retention and drawing posttests. Results of Study 2 showed main effects of generative drawing on retention, transfer and drawing posttests. However, in both studies the combination of generative drawing and provided pictures had no positive effect on learning outcome.

However, Schmeck (2010) also emphasize *instructional support before the drawing process.* According to Leutner and Leopold (2006), a combined training of the learning strategy and self-regulation aspects (received before the learning task) is a possible method to support the use of the drawing strategy. When learners monitor and control this cognitive learning strategy, namely the drawing strategy, their learning outcome should increase. Several studies regarding learning strategies showed that a combined training resulted in higher learning outcome in comparison to simple learning strategy trainings without focus on self-regulation or to no training (Leopold & Leutner, 2004, 2015; Leutner, Barthel, & Schreiber, 2001; Leutner & Leopold, 2006). Leopold (2009), for example, showed in a study concerning reading and understanding of a science text, that a combined training of generative drawing and self-regulation had a positive effect on learners' science text comprehension. Learners given the generative drawing strategy training only also performed better than the control group. However, the combined training had a positive effect on learners' ability to remember the learning content after three months.

Van Meter (2001) conducted a study concerning generative drawing wherein she varied the form of support. She found that the group with the most amount of support - provided illustrations and prompting questions to aid the comparison of their own drawing and the provided ones - scored significantly higher on a free recall test than the control group. In a later study, van Meter and colleagues (2006) used the same design as in the 2001 study but gave the control group (which did not draw) prompting questions that required comparison of the text and the provided illustrations. They also used a different learning text regarding birds' wings. The new learning text was chosen to give students a content with which they were familiar and their prior knowledge was higher. Van Meter and colleagues (2006) aimed to test the hypothesis that prior knowledge can be a form of support. The students in the drawing groups who received support (illustrations and/or prompting questions) scored higher on posttest outcomes than students in the control group. Students who drew pictures and compared them to accurate illustrations were better on posttest scores because they used the illustrations to get to know how their own drawings should look like and how detailed they should be. As a consequence, students were able to improve their drawings and in turn their mental models (van Meter & Firetto, 2013). Schmeck (2010) categorized this kind of external support as *instructional support after the drawing process.* Concerning the studies of Van Meter (2001) and Van Meter et al. (2006), this means that feedback on the quality of the self-generated drawings by means of a comparison with provided illustrations after the drawing process could improve the learning effect of drawing. On the one hand, according to Van Meter and Firetto (2013), provided illustrations serve as a *constraint function* "…because these illustrations helped learners know what their own drawings should look like" (Van Meter & Firetto, 2013, p. 265). On the other hand, Van

Meter and Firetto (2013) posit that the variation of support within the three drawing conditions in this study and the concurrent alteration when students have to draw with more or less support is interesting to look at. Van Meter (2001) found that students who get the most extensive support during drawing generated drawings with higher accuracy and also showed a greater number of self-monitoring events (as indicated by think-aloud protocols) than students with less support during drawing. Thus, this kind of support also served as a *self-regulation function*. To generate a drawing first and compare the drawing with an accurate provided illustration afterwards is a combination of learning with self-generated drawings and learning with provided illustrations (multimedia learning). However, the effectiveness of the strategy depends on the quality of the generated drawings, also called accuracy (see next section). The presentation of an accurate illustration concerning a learning text should trigger learners to compare their own drawings with the provided ones, using metacognitive processes. Mistakes in the self-generated drawings can then be revised (Winne & Perry, 2000). This metacognitive control usually has a positive effect on the understanding and learning of the to-be-learned content if the learner processes the given illustrations correctly and conducts all comparisons needed (Seufert, 2003).

In a study by Leutner, Leopold, and Sumfleth (2009) students were asked to read a chemistry text for comprehension (control group), draw a diagram concerning every paragraph in the drawing group or build up a mental model in the imagery group, and build up a mental model before drawing in the combination group. Leutner and colleagues find that drawing pictures decreased learning; the control group scored higher on learning outcome posttests. However, students in both drawing conditions showed increased cognitive load. Leutner and colleagues (2009) made the conclusion that this learning task wherein students had to generate a number of drawings was too effortful, so that the cognitive load was too high and overpowered any positive effects of the drawing strategy. In contrast, Firetto and van Meter (2011) also asked students to construct multiple drawings but found a positive learning effect for the drawing group. However, in this study students in the drawing group constructed seven diagrams but had 18 text paragraphs for which diagrams were provided, which served as support for students while drawing and learning with a complex biology text. To sum up, Firetto and van Meter (2011) showed that using the drawing strategy in learning tasks with highly demanding instructions is effective when students are supported adequately.

In summary, there is *instructional support during the drawing process*, like the provision of accurate provided cut-out figures for drawing, a provided drawing prompt or calling attention to specific parts of a learning text. There is also *instructional support before* *the drawing process,* for example, training of the learning strategy (generative drawing) and/or training of self-regulated learning aspects. Finally, there is *instructional support after the drawing process,* such as provided illustrations and prompting questions to aid students' comparison of their own drawings with provided ones.

Accuracy and Drawing

Several studies, including some described above, point to the accuracy of drawings, generated by students, affecting the learning outcome (Schwamborn, Mayer, et al., 2010; Schwamborn, Thillmann, et al., 2010; van Meter, 2001; van Meter, et al., 2006; for an overview see also van Meter & Garner, 2005). A sufficient accuracy, i.e., the quality of generated drawings, is positively correlated with students' learning outcome. The quality of the drawings or visualizations is high when learners have included in their drawings all relevant elements and have depicted the correct relations between elements described in the material. It is supposed that if learners recognize the important elements and their relations (Stern, Aprea, & Eber, 2003), they are also able to build up an internal mental model of the learning facts, which is important for deeper understanding of the learning content (van Meter & Garner, 2005). In this context, van Meter and Garner (2005) introduced the term *drawing accuracy.* Additionally, Schwamborn, Mayer, et al. (2010) established the *prognostic drawing principle*, which posits that the accuracy of learners' drawings during learning predicts the quality of their learning outcomes. When learning with text and provided pictures the quality of the provided pictures is given naturally, whereas during learning with text and generative drawing the accuracy of the pictures can vary between learners. In a study of van Meter and colleagues (2006), they found that the instruction to draw a picture enhanced the learning outcome of sixth-graders and fourth-graders in comparison to the non-drawing control group. Additionally, they found that participants in the most supported drawing condition achieved higher problem solving scores than participants who drew without support, when looking at the six-graders only. Lesgold and colleagues (1975) also found that first-graders did not benefit from just the instruction to generate pictures. However, they did benefit when correct cut-outs were given to them, which they could use for their drawings. Moreover, they found a positive correlation between the quality of the generated drawings and learning outcome. In the study by Schwamborn, Mayer, et al. (2010), already described above, it was also shown that students who generated drawings with high accuracy scored higher on learning outcome tests than students who generated drawings with lower accuracy. Whether learning with self-generated visualizations is successful seems to depend on learners' ability to create highly accurate drawings or visualizations. This is why support is important for students learning with the drawing strategy. Some studies described above in the support section refer to the quality of the drawings indirectly, namely by pointing to support that calls attention to specific parts of the text (Alesandrini, 1981) or using enough examples of visualizations to support learners in the drawing process in learning tasks with highly demanding instructions (Firetto & Van Meter, 2011). Both kinds of support have a constraint function; this means that these kinds of support aid the learner to know what their drawings need to include and how their drawings should look like to be highly accurate.

Cognitive Load and Drawing

According to the GTDC and the CMDC, drawing can trigger cognitive and metacognitive processes. On the one hand, this enhanced activation is assumed to result in deeper understanding of the learning material and, thus, to lead to better learning outcomes. However, on the other hand, the enhanced activation runs the risk of inducing additional cognitive load, which might stress the limited capacity of working memory and result in reduced learning outcomes (Chandler & Sweller, 1991; Leutner et al., 2009; Sweller, 2005). Accordingly, Leutner et al. (2009), as mentioned above, found that their drawing instruction seemed to be too intrusive and/or too difficult for students, as the participants in the drawing groups scored lower on learning outcome tests than did students who were asked to build up a mental model. Learners instructed to build up a mental model concerning the learning text stated to perceive less cognitive load by means of invested mental effort and perceived difficulty. Leutner et al. (2009) summarized that: "…what is intended to trigger helpful cognitive processing (drawing pictures for understanding in order to impose germane cognitive load on the learner and to help learning) entailed to impose extraneous cognitive load that hinders learning" (p. 288). This extraneous load requires cognitive resources, thus there is less space for germane cognitive load, resulting in hindered learning. According to Leutner et al. (2009) the extraneous load in this study is split attention (Ayres & Sweller, 2005) caused by switching back and forth between text and drawings. However, there are several studies showing a positive effect of generative drawing on learning. In other words, there are also studies on drawing that helps learning without imposing too much extraneous load. In contrast to the Leutner et al. (2009) study these studies support the learners' drawing process (e.g., Firetto & van Meter, 2011; Lesgold et al., 1975, 1977; Schwamborn, Mayer, et al., 2010; Schwamborn, Thillmann, et al., 2010; van Meter, 2001; van Meter et al., 2006).

In sum, it seems to be important to use well-created learning material (considering the principles of multimedia design), meaning well structured learning texts and functional drawing mechanisms and to give sufficient support so that extraneous cognitive load is minimized and learners are able to profit from the drawing process.

1.9 The Research Gap

Although research has produced mixed results regarding the efficacy of the generative drawing strategy, it can be summarized that paper-and-pencil-based generative drawing has a positive impact on the learning outcome if the following aspects are taken into consideration: At first students need to be supported during the drawing process, second the learning material needs to be presented in a way that facilitates working with it (considering the principles of multimedia design) and third the learning material needs to guide the learners in their generation process as well as that they are able to create accurate drawings without being cognitively overloaded. Consequently, cognitive resources are available and generative processing can take place during drawing, fostering deeper understanding of the to-be-learned information.

However, working with computers within school lessons has become a topical subject. On the one hand computer-based learning offers a lot of options to process information actively, on the other hand it is supposed to increase students' motivation. Thus, it is obvious to use successful learning strategies, like the generative drawing strategy, within computer-based learning. However, while there have been several paper-based learning studies on generative drawing, to our knowledge only one study has investigated this kind of drawing for computer-based learning (by means of drag-and-drop), and it did not find support for the benefits of generative drawing (Schwamborn et al., 2011). There is no complementary evidence that the benefits of generative drawing can be transferred to computer-based learning environments. Thus, research is necessary to investigate whether the generative drawing strategy can be used as successful learning strategy within computer-based learning, as well.

Looking at the study of Schwamborn and her colleagues (2011) in detail, this study investigated whether the learning outcome from science texts can be increased by providing learners with different forms of computer-based visualizations. Students read a text about the chemistry of washing with soap and water on the computer. Instructions varied so that there were four different groups. Besides a control group wherein the participants only read the text, one group was instructed to generate drawings concerning the important occurrences in each paragraph of the text. Another group got the text to read as well as provided visualizations for every paragraph of the text. The last group generated their own drawings and saw the provided ones after drawing to compare them. After learning with the material, students answered questions on cognitive load (mental effort, perceived difficulty) and worked on comprehension posttests (retention, transfer, drawing). Although results showed positive main effects of provided visualizations on all three comprehension measures and negative main effects on both cognitive load measures, there was only one positive main effect of generative drawing on the drawing posttest, which is not surprising. Additionally, self-generated drawing increased mental effort. Taken together, Schwamborn et al. (2011) could not show that self-generated drawing has a positive effect on students' comprehension when the drawing was computer-based by means of drag-and-drop, i.e., moving the pointer to the selected drawing element, press the button on the mouse or trackpad to 'grab' the element, then drag the element to the desired location by moving the pointer to this one and finally 'drop' the drawing element by releasing the button. Instead, students seem to have less cognitive resources available for generative processing and thus, generating drawings seems to increase extraneous cognitive load.

However, the study of Schwamborn et al. (2011) has some shortcomings. First, students within this study learned with a computer-based learning environment they were not experts in. According to CLT (Sweller, 1999, 2005) this could lead to too much extraneous cognitive load, which in this study is reflected by means of increased mental effort and learning time within the groups who generated drawings on their own. Too much extraneous load leads to less cognitive resources available for generative processing, respectively for meaningful learning (Mayer, 2009; Sweller, 1999, 2005). Second, learning outcomes were only tested immediately after learning, which could be different in a realistic learning situation. The same is true for the cognitive load measures, which were only tested once after learners finished the learning environment completely. Third, Schwamborn et al. (2011) tested the generative drawing strategy with only one specific learning content, namely the chemistry of washing with soap and water. Finally, in their study computer-based generative drawing was done by moving and combining provided elements on the computer screen. Regarding research on generative drawing so far, it might be assumed that moving and combining the elements is not the same as drawing by hand on paper with a pencil.

Additionally, to our knowledge there is no study wherein a comparison was made between learning with the drawing strategy by hand on paper and computer-based by means of drag-and-drop. Thus, research is needed to specify the underlying processes of generating drawings paper-and-pencil-based versus computer-based by means of drag-and-drop. The following studies are intended to fill this research-gap.

1.10 Structure and Research Questions

Two empirical studies on generative drawing concerning science texts will be presented in the following chapters. One study on computer-based generative drawing concerning two different science texts and online measured cognitive load and a second study comparing paper-based and computer-based generative drawing will be presented, followed by a general discussion of both studies. Taken together, the studies present a stepwise approach to analyze the effect of computer-based drawing: at first whether generative drawing by means of drag-and-drop on a computer screen can increase learning from science texts generally; second which kind of effect computer-based generative drawing has on students' cognitive load; and finally whether benefits of generative drawing are the same for paper-based and computer-based materials.

In Study I students are asked in two lessons to read science texts (chemistry and biology) either with provided illustrations concerning the main ideas of the text (illustration group), or with the instruction to generate their own drawings concerning the main ideas of the text on a computer by means of drag-and-drop (generation group), or both (generation + illustration group), or neither (control group). This study provides partly a replication of the study by Schwamborn et al. (2011). However, in the present study training tutorials are extended, follow-up learning outcome posttests are included, cognitive load is measured online (meaning immediately and continuously after each learning text paragraph), a second biology learning content is used, and finally the drawing tools are optimized in general. These changes are made to eliminate shortcomings of the study by Schwamborn et al. (2011). In sum, Study I is intended to investigate the following:

- First, based on theoretical assumptions on the learning strategy of drawing and negative results of a study by Schwamborn and her colleagues (2011), the study investigates whether students learn better from a science text (computer-based) when they are asked to generate drawings (computer-based) representing the main ideas of the text. Thus, the aim is to know if the *generative drawing principle*, introduced by Schwamborn, Mayer, et al. (2010), can be extended to computer-based learning when students are instructed to draw using a computer-based interface.
- Second, the study aims to test the generalizability of the *prognostic drawing principle* to computer-based generated drawings, which posits that the accuracy of learners' drawings during learning predicts the quality of their learning outcomes.
- Third, although the drawing activity is implemented in a way that minimizes extraneous activity (providing students with a toolbar including all relevant

drawing elements and a drawing background), the study seeks to determine if students report higher cognitive load when they are asked to draw visualizations using a computer-based interface while reading a science text and if there is an influence of cognitive load on the generative drawing effect. For this reason, cognitive load is measured online (meaning immediately and continuously after working with each section of a learning task).

- Fourth, the study is expected to replicate the multimedia effect.
- Fifth, besides separately testing the effect of learning with either generated drawings or provided illustrations, the effect of a combination of these two strategies is investigated. This is incorporated because of the assumption of van Meter (2001) and van Meter and colleagues (2006) that provided illustrations show learners how their drawings should look like and thus serve as support. Additionally, the study investigates whether the results of Schwamborn, Thillmann, et al. (2010), namely that there is no effect of a combination of provided illustrations and generative drawing on learning outcome, can be replicated.
- Finally, differences in the amount of study time between the groups are investigated. It is expected that students need more study time when they are asked to generate visualizations while reading a science text on the computer compared to students who do not generate pictures.

Study II investigates the effect of generative drawing only. It is the first study to compare the effects of the drawing strategy when students generate drawings with paper and pencil to using a computer by means of drag-and-drop. Students are asked to read a 6-paragraph chemistry text in which paragraphs were alternately presented on paper (with instructions to create a drawing by hand concerning the content of the science text paragraph) and on a computer screen (with instructions to use a drag-and-drop interface to create a drawing concerning the content of the science text paragraph). On a subsequent questionnaire students are asked about their ratings on different cognitive, metacognitive and mechanical difficulties that could occur while using the drawing strategy. Additionally, the questionnaire contains questions concerning students' enthusiasm respectively motivation.

- First, the study examines if learning outcomes are higher when reading and generative drawing are computer- or paper-based. Hence, in this study, every student learns with science text paragraphs that are alternately presented on paper and on the computer screen.

- Second, the study investigates which kind of medium (paper vs. computer) and respectively which kind of drawing mechanics (hand drawing vs. drag-and-drop) students perceive as more difficult, i.e., which medium causes higher cognitive load.
- Third, the study aims to test whether the quality of learners' drawings during learning predicts their learning outcomes, independent of the medium in which the drawings are generated.
- Finally, possible explanations for differences in the effectiveness of the generative drawing principle based on whether students draw by hand versus on the computer will be examined. Therefore, a questionnaire was designed to get a deeper look at components possibly underlying the construct of cognitive load. Especially of interest is what underlies students' perceived task difficulty, such as different cognitive, metacognitive and motoric difficulties. As a practical aim of this study, recommendations on how to successfully implement the generative drawing principle in the future are provided.

In the final chapter, a brief overview of all the studies' results followed by a joint discussion regarding the empirical, theoretical and practical implications of the studies is given. Finally, an outlook on future research is provided.

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2 Study I: Extending the Generative Drawing Principle to Computer-Based Learning

Abstract

This study investigated whether the generative drawing principle (i.e., creating drawings while reading a scientific text causes generative processing that leads to better learning outcomes) and the prognostic drawing principle (i.e., the accuracy of the generated pictures correlates positively with the learning outcome) can be applied to computer-based learning. Two hundred and forty-nine German 8th graders in higher track secondary school read two onscreen texts dealing with chemistry and biology. This was followed by posttests of transfer, retention, and drawing as measures of learning outcomes. The study followed a 2 x 2 x 2 factorial design, with generative drawing (whether or not students generated drawings) and instructor-provided illustration (whether or not illustrations were provided) as between-subjects factors and the content of the lesson (chemistry or biology) as a within-subjects factor. The results for both lessons combined were consistent with the generative drawing principle: Students who were instructed to generate pictures during learning scored higher on learning outcome tests of transfer (d = 0.30) and drawing (d = 0.77), but not on retention (d = 0.16). Additionally, the results provide strong and consistent support for the prognostic drawing principle, in which the accuracy of the pictures made during learning correlates positively with posttest scores on transfer (r = .51), retention (r = .41), and drawing (r = .52). Thus, the results suggest that the generative drawing principle and the prognostic drawing principle can be extended to computer-based learning environments, when extraneous processing caused by the specific mechanics of generating computer-based drawings is reduced.

Keywords: text comprehension, generative drawing, multimedia learning, cognitive load

2.1 Introduction

Suppose a student is reading a scientific text on a computer screen. Simply sitting in front of a screen and reading may seem too passive, especially since computer-based learning offers so many options for active information processing. Thus, we might think about ways of prompting the learner to engage in deeper cognitive processing during learning. One learning strategy intended to foster generative processing is to ask the student to draw an onscreen illustration of the content presented on each page, using a computer-based drawing interface. Although it has been demonstrated that learning from paper-based texts can be improved when students engage in hand drawing using paper and pencil (Leopold & Leutner, 2012; Schmeck, 2010; Schwamborn, Mayer, Thillmann, Leopold, & Leutner, 2010; Schwamborn, Thillmann, Leopold, Sumfleth, & Leutner, 2010; van Meter & Garner, 2005), there is no complementary evidence that the benefits of generative drawing extend to computer-based learning environments (Schwamborn, Thillmann, Opfermann, & Leutner, 2011). Both hand-made drawings and computer-based drawings can also be called 'visualizations'.

The primary goal of the present study is to test the generality of the generative drawing principle, which posits:

> People learn better from a science text when they are asked to draw illustrations representing the main ideas of the text. An important boundary condition is that the drawing activity should be implemented in a way that minimizes extraneous activity by the learner, such as provision of drawings of all key elements and a background for the drawing (Schwamborn et al., 2010, p. 878).

Additionally, we aimed to test the generality of the prognostic drawing principle, which posits that the accuracy of learners' drawings during learning predicts the quality of their learning outcomes. In short, the present study seeks to determine whether the generative drawing principle and the prognostic drawing principle can be extended to onscreen learning environments in which students are instructed to draw using a computer-based interface.

2.2 Theory and Predictions

The scenario of drawing while reading an onscreen scientific text, as described in the foregoing paragraph, can create two competing demands on the learner's information processing system—*generative processing* and *extraneous processing* (Mayer, 2009; Sweller, Ayres, & Kalyuga, 2011). On the positive side, the act of translating printed words into a pictorial representation, such as when the learner is asked to produce drawings, can prime a form of generative processing during learning—that is, processing aimed at making sense of the material by selecting important material, mentally organizing it into a coherent structure, and integrating it with relevant prior knowledge. This is the rationale for support for the generative drawing principle that has been demonstrated with hand-drawing with paper and pencil (Leopold & Leutner, 2012; Schmeck, 2010; Schwamborn, Mayer, et al., 2010; van Meter & Garner, 2005). On the negative side, figuring out how to use a cumbersome computer interface for generating onscreen drawings can create an excessive load of extraneous processing: That is, processing that does not support the learning objective but wastes precious cognitive capacity. Indeed, this may be the reason why support is lacking for the generative drawing hypothesis in computer-based environments (Schwamborn et al., 2011).

The challenge of instructional design in this scenario is to create a drawing experience that (a) fosters generative processing by asking learners to translate words into graphics, and (b) minimizes extraneous processing by ensuring that the drawing interface is easy to use. In the present experiment, we attempted to foster generative processing by asking learners to create an onscreen drawing below the onscreen text for each page, and also to minimize extraneous processing by providing learners with a pre-drawn background and a set of pre-drawn elements that learners could drag-and-drop onto the background; a general approach developed in a prior study (Schwamborn et al., 2011). In short, to minimize the cognitive demands of the drawing mechanism we provided a drawing prompt: that is, a toolbar with all the relevant elements students needed to draw the pictures and a drawing background. A tutorial and pretraining were also supplied, so as to make students familiar with the drag-and-drop drawing mechanism of the computer-based learning environment.

To the degree to which the instructional design is successful in fostering generative processing while minimizing extraneous processing, we predict a generative drawing effect in which students who are asked to generate computer-based drawings during learning will outperform those who are not, on posttest measures of transfer, retention, and drawing. The effort required to create drawings might also be reflected in higher levels of reported mental effort and perceived difficulty. Additionally, to the degree to which the instructional design is successful in fostering generative processing while minimizing extraneous processing, we predict a prognostic drawing effect in which the accuracy score of student-generated drawings during learning correlates positively with posttest scores on transfer, retention, and drawing. Thus, we predict that the accuracy of the learners' drawings during learning can predict performance on the posttests. This means that students with a high-accuracy score are expected to perform better on learning outcome scores than students with a low-accuracy score.

In our study we asked students in two lessons to read science texts (chemistry and biology) presented within a computer-based learning environment, either with provided illustrations concerning the main ideas of the text (illustration group), or with the instruction to generate their own drawings concerning the content of the science text (generation group), both (generation + illustration group) or neither (control group). Although we included instructor-generated illustrations in the study to provide a broader context, our main focus was on whether or not generative drawing fosters deeper learning.

2.3 Theoretical Background

Reading scientific texts usually entails cognitively highly demanding processes of text comprehension and thus is subject to the risk that students will fail to engage in deep processing of the material. One technique intended to foster deeper processing of scientific texts is to ask students to generate drawings of the important events described in the text: This can be termed the learner-generated drawing strategy (Alesandrini, 1984; Schmeck, 2010; Schwamborn, Mayer, et al., 2010; van Meter & Garner, 2005). Recent research on generative processing has revealed that instructing students to draw pictures by hand during learning results in improved performance on learning outcome posttests (Leopold, 2009; Leopold & Leutner, 2012; Schmeck, 2010; Schwamborn, Mayer, et al., 2010; see also van Meter, 2001). A serious limitation of research on the learner-generated drawing strategy is that while benefits for text comprehension have been documented when learners draw by hand using paper and pencil (Leopold & Leutner, 2012; Schwamborn, Mayer, et al., 2010; see also van Meter, 2001; van Meter, Aleksic, Schwartz, & Garner, 2006), to our knowledge, only one study has investigated this kind of drawing for computer-based learning (by means of drag-and-drop); and did not find support for the benefits of generative drawing (Schwamborn, et al., 2011). This apparent contradiction is the motivation for the present study.

Asking students to generate visualizations that reflect the main ideas of each paragraph is a learning strategy, called the learner-generated drawing strategy. A learning strategy is an activity that learners engage in during learning, with the intention of improving their learning of the material presented (Weinstein & Mayer, 1986). In this study we used a computer-based generative drawing to increase generative processing and to support students in comprehending our scientific material. In drawing, students have to translate the verbal text information into a picture that represents spatial relationships among the elements referred to in the text (Carney & Levin, 2002). This generation process enhances active processing of the to-be-learned information on a cognitive level, as well as on a metacognitive level (van Meter & Garner, 2005), corresponding to *generative processing* in the Cognitive Theory of

Multimedia Learning (CTML; Mayer, 2009) and *germane load* in Cognitive Load Theory (CLT; Chandler & Sweller, 1991; Sweller, Ayres, & Kalyuga, 2011; Sweller, van Merriënboer, & Paas, 1998). Studies in which the learners' construction of drawings was instructionally supported (Schwamborn, Mayer, et al., 2010; van Meter & Garner, 2005) showed benefits of the drawing strategy on text comprehension, whereas studies without instructional support for drawing did not (Alesandrini, 1981; Leutner, Leopold, & Sumfleth, 2009). According to these studies, asking students to generate drawings runs the risk of creating too much extraneous cognitive processing (or extraneous cognitive load): that is, cognitive processing that does not serve the instructional objective. This might lead to fewer cognitive resources being available for generative processing (or germane cognitive load), that are needed for deep-level understanding (Mayer, 2009).

Additionally, other studies have investigated the accuracy of learner-generated drawings (e.g., Lesgold, Levin, Shimron, & Guttmann, 1975; Lesgold, de Good, & Levin, 1977; Schmeck, 2010; Schwamborn et al. 2010; Stern, Aprea, & Ebner, 2003; van Meter, 2001; van Meter et al., 2006), meaning "the degree to which completed drawings resemble the represented object(s)" (van Meter & Garner, 2005, p. 299). Overall, the results showed that students who generated high-accuracy drawings also scored higher on learning outcome tests than those who generated low-accuracy drawings.

The generative theory of drawing construction (van Meter & Garner, 2005) states that asking students to draw pictures while reading a text leads them to engage in different cognitive processes: namely, selection, organization and integration. In concrete terms, this means that students, who are assigned a text and are asked to draw a picture corresponding to the main ideas described in the text, have to select relevant ideas, elements and relationships first. After that, they have to organize the information to build their own internal verbal model. Finally, students have to construct an internal pictorial representation of the text's information and integrate it with the verbal model and with relevant prior knowledge.

Integration of the internal verbal and pictorial representations into a coherent mental model is important, because it is the basis for generating an external visualization (van Meter & Garner, 2005). If students have problems in building a mental model or an external visualization, they can monitor themselves and go back to their internal verbal representation or even back to the original text (van Meter, 2001). Thus, the generation of drawings seems to encourage students to engage in cognitive and metacognitive processing and thus fosters deep-level understanding (van Meter, 2001; van Meter & Garner, 2005; van Meter et al., 2006). However, generating one's own drawing runs the risk of creating too much extraneous cognitive processing (or extraneous cognitive load), leading to fewer cognitive resources being available for generative processing (or germane cognitive load), which is needed for deep-level understanding (Mayer, 2009).

2.4 Method

Participants and Design

In this study participants were 249 German 8th graders from higher track secondary schools who provided complete data and whose study time was within two standard deviations above or below the mean study time of their respective group. Their mean age was 13.2 years (SD = 0.5); 53.2 % were female. The study followed a 2 x 2 x 2 factorial design with generative drawing (whether or not students generated drawings) and instructor-provided illustration (whether or not illustrations were provided) as between-subjects factors and content (chemistry or biology) as a within-subjects factor. Fifty-nine students were in the control group, 73 were in the generation group, 56 in the illustration group, and 61 were in the generation + illustration group. All groups received both a biology science text and a chemistry science text in counterbalanced order of paragraphs.

Materials and Apparatus

The computer-based materials consisted of four versions of two lessons: one dealing with the chemistry of washing with soap and water (approximately 1000 words) and one dealing with the biology of the flu (approximately 850 words). The chemistry science text consisted of six screen pages, each containing one paragraph about the causal steps in the process of mixing soap and water (Figure 2.1). The chemistry science text and related material was taken from Schwamborn et al. (2011) and adapted for the present study. The biology science text consisted of seven screen pages each containing one paragraph about the causal steps in catching and having the flu (Figure 2.2). The content of the biology science text and related material was taken from Schwamborn, Opfermann, Pfeiffer, Sandmann and Leutner (2012) and adapted for the present study.

In the lesson for the control group, one paragraph of text was presented at the top of each slide. In the lesson for the illustration group, each slide contained a text paragraph at the top and a picture of the content on the righthand bottom side. The provided illustrations were static functional pictures representing the main ideas of each paragraph, and consisted of pictorial elements identical to those provided in the drawing prompt used in the generation group.

In the lesson for the generation group, each slide contained a text paragraph on top and a drawing prompt on the bottom left side. This drawing prompt included two parts: (1) a toolbar showing all the relevant pictorial elements, as described in the text, for generating a drawing for the respective text paragraph by means of drag-and-drop: moving and combining the elements on the computer screen, and (2) a partly pre-drawn background into which the elements could be placed.

In the lesson for the generation + illustration group, each slide contained a text paragraph on top, the drawing prompt on the bottom lefthand side, and an additional button for clicking after having generated the drawing. After this button was clicked, an illustration representing the main ideas of the paragraph appeared on the bottom righthand side, and students were instructed to compare their generated drawing with the provided illustration (which was the same as in the illustration group). The additional button was blocked for approximately two minutes, to prevent students from clicking immediately, without first generating their own drawing.

For all groups, each lesson was preceded by a three-slide tutorial, presented before the chemistry or biology content screen pages, teaching students how to use the drag-and-drop interface to make drawings. In the first slide, students were asked to draw a little man by means of the given elements; in the second slide students were asked to move and rotate different sized hearts to the right place to fill in holes, and in the third tutorial slide, students were asked to build an isosceles triangle with the help of given elements.

Additionally, after each slide a prompt asked the participants to rate their perceived difficulty and mental effort in a cognitive load booklet. At the end of the learning experience, participants were asked to rate overall difficulty and mental effort as well as answer a question about the drag-and-drop interface, on the final page of the cognitive load booklet. The apparatus consisted of 35 Dell computer systems on which the learning environment was installed.

The paper-based materials consisted of the participant questionnaire, a prior knowledge pretest, a verbal ability pretest, spatial ability pretest, motivation survey, two cognitive load booklets, and two learning outcome posttests. The participant questionnaire solicited demographic information, asked students to report their biology and chemistry school grades and to rate their use of computers. The prior knowledge test consisted of four short-answer items, with two items related to the content of the chemistry science text and two items related to the content of the biology science text. An example of a biology question is: “Describe how the flu can invade your body and how it breeds.” The verbal ability pretest consisted of 20 verbal analogy problems adapted from the Verbal Analogies subscale of the Cognitive Capability Test (Heller & Perleth, 2000). The spatial ability pretest consisted of 10 paper folding items taken from the Paper Folding Test in the Kit of Factor-Referenced Cognitive Tests (Ekstrom, French, & Harman, 1976). The motivation survey consisted of nine items taken from the Challenge and Interest subscale of the Questionnaire to Assess Current Motivation in Learning Situations (FAM; Rheinberg, Vollmeyer, & Burns, 2001). An example of such an item is: “This task was a real challenge for me.” Each item was rated on a 7-point Likert scale, with responses ranging from *that is not right* to *that is right*.

As a dependent variable, which could also serve as a potential mediator of the effects of the experimental factors on the students’ learning performance, the amount of cognitive load experienced during learning in the learning environment was assessed online after each computer slide with two items: one asking the learners to rate their perceived task difficulty on a 7-point scale (Kalyuga, Chandler, & Sweller, 1999) and one asking them to rate their invested mental effort on a 7-point scale (Paas, 1992). The cognitive load booklet for the chemistry science text had six pages, while the booklet for the biology science text had seven pages, with both the perceived difficulty and the mental effort item on each page. Additionally, after students finished working with the learning environment, they again rated their overall learning experience with regard to perceived difficulty and mental effort, and they answered a question concerning the usability of the drag-and-drop mechanism on a separate page.

The three learning outcome posttests for each lesson were the retention, transfer, and drawing tests. The chemistry retention test consisted of 13 multiple-choice items (Cronbach’s $\alpha = .69$), such as: “What is a water molecule surrounded by on the water’s surface?: (a) by water molecules (b) by air molecules (c) by water molecules and air molecules (d) by water molecules and oxygen molecules.” The biology retention test consisted of 19 multiple-choice items (Cronbach’s $\alpha = .84$), such as: “What is part of a scavenger cell?: (a) nucleus, capsule and pseudopodia (b) cell membrane, nucleus and pseudopodia, (c) cell membrane, antibodies and pseudopodia, or (d) nucleus, antibodies and pseudopodia.” The retention tests assessed students’ retention of factual and conceptual information covered in the text.

The chemistry transfer test consisted of three open-ended questions (Cronbach’s $\alpha = .84$), such as: “Pure water has a high surface tension. Please explain how the surface tension is created.” The biology transfer test consisted of four open-ended questions (Cronbach’s $\alpha = .70$), such as: “Describe the two steps of the immune response, which are necessary to form antibodies after the cell has absorbed and decomposed the virus." The transfer tests assessed students' ability to apply information presented in the text to new situations.

The drawing tests asked students to draw sketches depicting key elements and the spatial relations among them, using paper and pencil. The chemistry drawing test consisted of three items (Cronbach's $\alpha = .70$), such as: "Please make a drawing that shows the impact adding soap has on the surface tension of water". The biology drawing test consisted of four items (Cronbach's $\alpha = .70$), such as: "Draw the bond between three influenza viruses and matching antibodies". All materials were in the German language.

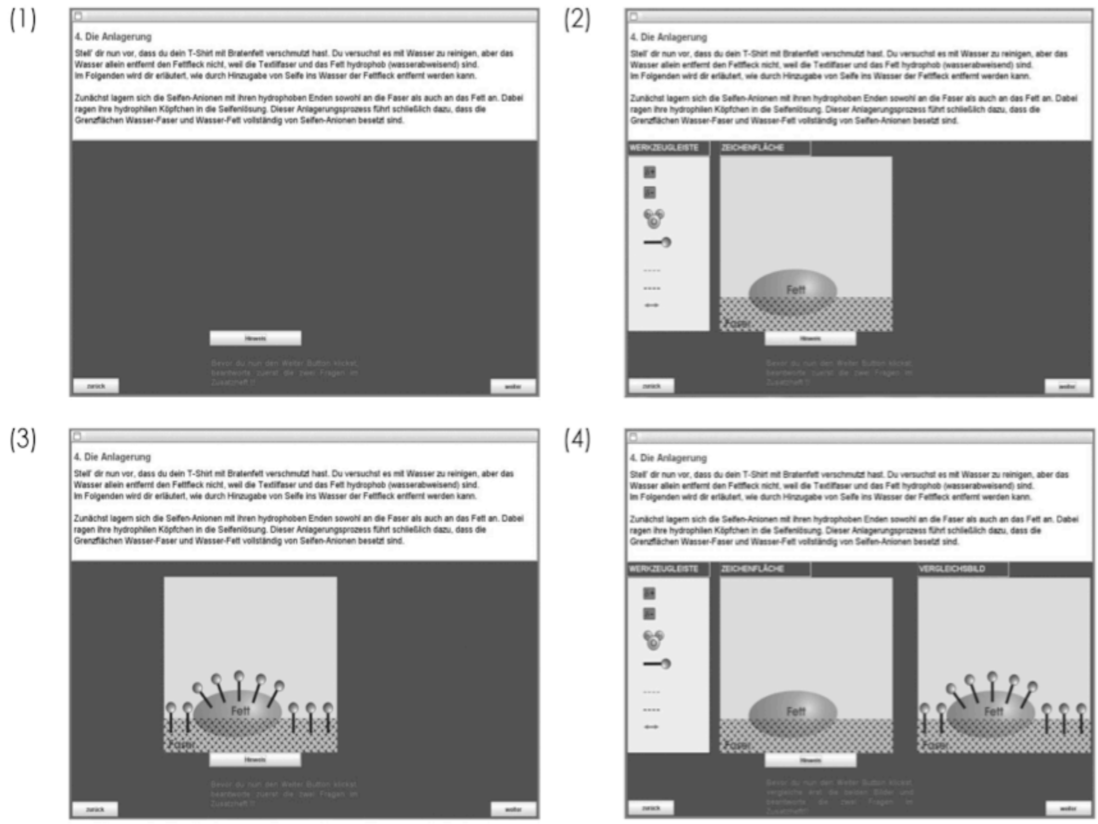

Figure 2.1 Example frames of the computer-based chemistry science text for control group (1), generation group (2), illustration group (3); and generation + illustration group (4) (German version).

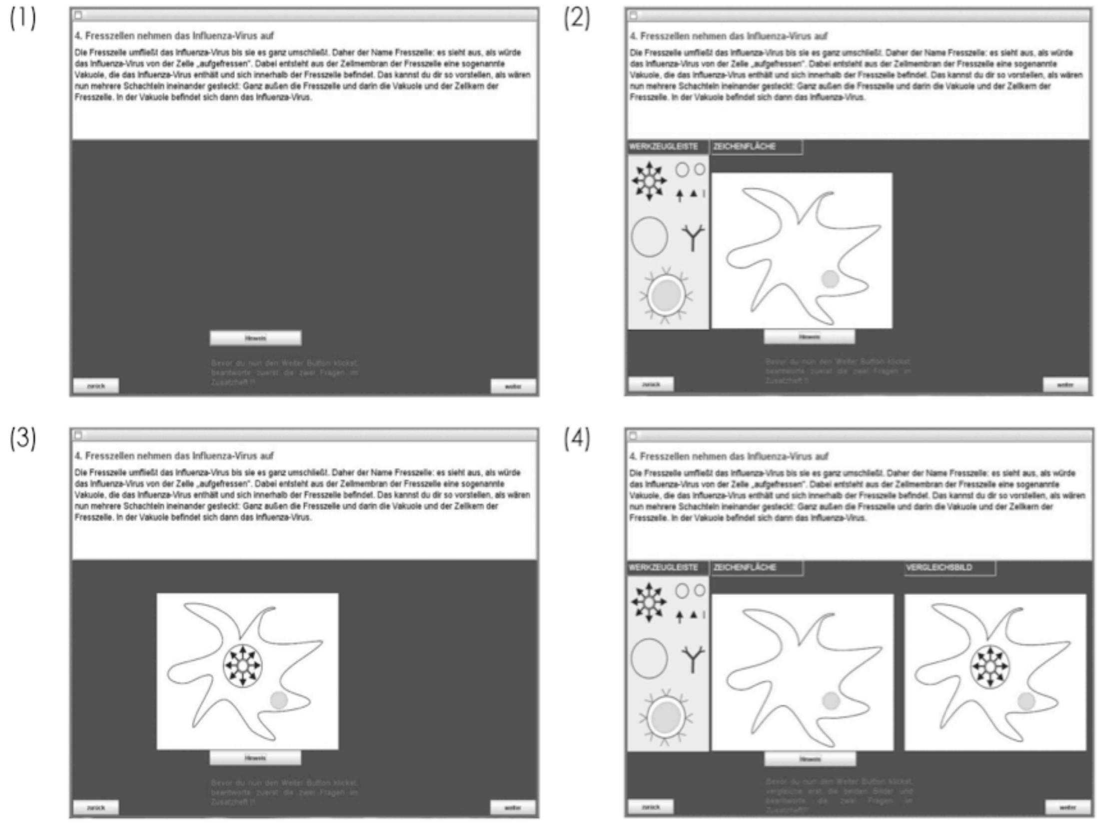

Figure 2.2 Example frames of the computer-based biology science text for control group (1), generation group (2), illustration group (3); and generation + illustration group (4) (German version).

2.5 Procedure

Within their classes, students were randomly assigned to treatments. To ensure that students in both drawing groups did not feel rushed when students in the non-drawing groups completed the task more quickly, groups were tested in separate classrooms. The study was distributed across three consecutive days.[1] On the first day, students first completed the participant questionnaire and the prior knowledge test at their own pace. They were then given the spatial ability pretest, with a three-minute time limit, and the verbal ability pretest, with a seven-minute time limit. On the second day, students were given the first computer-based lesson. This procedure was counterbalanced: that is, half of each class received the chemistry science text first and the other half received the biology science text first. Each student had about 10 minutes to work with the tutorial section before starting with the learning section. All students were instructed to read the science text for comprehension. Additional instructions varied according to the conditions. Students in the generation group were instructed to read the text and to make drawings (using the drawing prompt on the

[1] The same posttests for both lessons were administered six weeks later, but the data are not included in this study, since some students failed to engage in taking the same tests over again.

computer screen) representing the main ideas of each text paragraph. Students in the illustration group were instructed to read and additionally to look at provided visualizations representing main ideas of the text. Students in the generation + illustration group were instructed to read, to draw (using the drawing prompt), and finally to compare their visualizations to those provided. Students in the control group were only instructed to read the text for comprehension.

For each lesson, students completed the motivation survey after the tutorial section and after the learning section of the lesson. To assess cognitive load online (i.e., during learning), students were instructed to answer the two items measuring mental effort and perceived difficulty in the cognitive load booklets next to their computer after each text paragraph. Additionally, they received both cognitive load items again, plus one question concerning the drag-and-drop mechanism after they had finished learning with all text paragraphs. Total study time was recorded for each lesson.

Finally, students received the transfer, drawing, and retention tests to complete at their own pace, without access to the learning materials. Overall, after instructions and the tutorial, students had approximately 70 minutes to learn in the computer environment and to finish the posttests. They could decide on their own when they were finished with the learning and subsequently, when they were finished with the posttests. When students finished their learning they received the posttest immediately, meaning that the time between learning and the posttests was the same for every subject.

The third day followed the same pattern as the second day, with every student staying in his/her condition but working with the remaining lesson. This research was conducted in compliance with APA ethical principles.

2.6 Results

Scoring

The chemistry prior knowledge score for each participant was determined by counting the total number of correct main ideas for each of the two questions of the chemistry prior knowledge test, based on a scoring rubric consisting of six idea units. The biology prior knowledge score for each participant was determined by counting the total number of correct main ideas to each of the two questions of the biology prior knowledge test, based on a scoring rubric consisting of six idea units. Students' answers were scored by two student assistants specialized in science education, with satisfactory inter-rater agreement for chemistry prior knowledge (Goodman-Kruskal gamma = .93) and for biology prior knowledge (Goodman-Kruskal gamma = .99).

The spatial ability score was determined by tallying the number correct out of 10; the verbal ability score was determined by tallying the number correct out of 20, and the motivation score was determined by tallying the nine ratings to yield a total score for motivation. Overall, there were two motivation scores for the first lesson and two for the second lesson; one prior to studying the lesson and one after learning.

We computed the chemistry transfer test score for each learner by counting the total number of correct solution ideas in written answers to each of the three open-ended questions out of twelve possible ideas. We computed the biology transfer test score for each learner by counting the total number of correct solution ideas in written answers to each of the four open-ended questions out of nine possible ideas. Students' answers were again scored by the two student assistants, with satisfactory inter-rater agreement on the chemistry transfer test (Goodman-Kruskal gamma = .87) and on the biology transfer test (Goodman-Kruskal gamma = .86).

We computed the chemistry and biology retention test scores for each learner by awarding 1 point for each correct answer, and we added up the points for each question to compute the total retention scores for each test, out of a total possible 13 on the chemistry retention test and 19 on the biology retention test.

We computed the chemistry and biology drawing test scores by counting the total number of correct main ideas in each learner's answer across the three items on the chemistry drawing test and the four items on the biology drawing test, respectively. Students could earn a maximum of 15.5 points on the chemistry drawing test and 21 points on the biology drawing test. Students could end up with half points, because it is possible to draw only one part of an element correctly. Students' answers were scored by the two student assistants, with satisfactory inter-rater agreement on the chemistry drawing test (Goodman-Kruskal gamma = .85) and on the biology drawing test (Goodman-Kruskal gamma = .89).

Finally, in order to assess the quality of learner-generated visualizations constructed by both generation groups during learning in each lesson, we computed a drawing accuracy score for each of the six drawings for the chemistry science text and each of the seven drawings for the biology science text, yielding a maximum of 27 points on chemistry drawing accuracy and 21 points on biology drawing accuracy. The two student assistants scored each learner-generated visualization for each student, with satisfactory inter-rater agreement on the chemistry drawing accuracy test (Goodman-Kruskal gamma = .80) and on the biology drawing accuracy test (Goodman-Kruskal gamma = .84). In order to compare performance across the various tests on a common metric, we computed the proportion correct on each test by dividing each student's obtained score by the total possible score.

Are the Groups Equivalent on Basic Characteristics?

Before examining treatment effects on learning outcome measures, we analyzed whether the four experimental groups differed on some basic characteristics. Chi-square analysis and analyses of variance, based on alpha = .05, indicated that there were no significant differences among the groups in the proportion of males and females, chemistry prior knowledge score, biology prior knowledge score, spatial ability score, verbal ability score, or motivation score. Overall, we concluded that the groups were equivalent on basic characteristics.

Do Students Learn Better When They Are Asked to Generate Drawings While Reading a Science Text?

The major goal of this study was to determine if asking students to generate computer-based drawings while reading a science text in a computer-based learning environment is an effective learning strategy that promotes improvements in posttest performance. In short, the goal was to determine whether computer-based drawing could produce a generative drawing effect similar to the one found with paper-and-pencil drawings, in which generating drawings while reading a science text enhanced learning outcomes (Schwamborn, Mayer, et al., 2010).

A multivariate analysis of Variance (MANOVA), with generation and illustration as factors and posttest scores (transfer, retention, drawing) for each science text (chemistry, biology) as the dependent variable, showed that there was a significant effect of generation on the posttest scores, $F(6,240) = 12{,}85$, $p < .001$. Table 2.1 summarizes the mean proportion correct (and standard deviations) on the three posttests for the chemistry science text. The primary research issue concerns whether there is a generative drawing effect in which students who draw while learning perform better on posttests than those who do not. The left portion of Table 2.1 shows the mean proportion correct and standard deviations on the transfer test for students in the four groups. A separate univariate analysis of variance (ANOVA), with generation and illustration as factors and posttest scores as the dependent variable, indicated a positive main effect of generating drawings on the transfer scores, $F(1, 245) = 8{,}82$, $p = .003$, $d = .39$, in which the two generation groups (M = 19.5% correct, SD = 19.1) significantly outperformed the two groups that did not generate drawings (M = 12.6% correct, SD = 16.1). The middle portion of Table 2.1 summarizes the mean proportion correct and standard deviations on the retention test for the four groups. No significant main effect of generating visualizations was found on the retention test of the chemistry science text, $F(1, 245) = 0.64$, $p = .423$, $d = .11$: That is, the proportion correct for the generation groups (M = 51.0% correct, SD = 22.1) did not differ significantly from the groups that did not generate drawings (M = 48.6% correct, SD = 22.5). The right portion of Table 2.1 shows the mean proportion correct on the drawing test for the four groups. There was a positive main effect of generating visualizations on the drawing scores, $F(1, 245) = 48,97$, $p < .001$, $d = .79$, in which the groups that generated illustrations (M = 39,8% correct, SD = 29.9) significantly outscored those that did not (M = 18.4% correct, SD = 23.9). There were no significant interactions.

Table 2.1
Mean Proportion Correct (Standard Deviation) on the Chemistry Transfer Test, Chemistry Retention Test, and Chemistry Drawing Test for all Four Groups

		Type of test					
		Transfer		Retention		Drawing	
Group	*n*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Control	59	.14	.16	.52	.22	.06	.11
Illustration	56	.11	.16	.45	.23	.32	.26
Generation	73	.21	.20	.53	.21	.30	.23
Generation + illustration	61	.18	.18	.49	.23	.51	.33

Table 2.2 summarizes the mean proportion correct and standard deviations on each of the three posttests for the biology science text. The left portion of Table 2.2 shows the mean proportion correct and standard deviations on the transfer test for the four groups. A separate ANOVA indicated that the proportion correct on the transfer test by the generation groups (M = 14.4% correct, SD = 16.3) did not differ significantly, $F(1, 245) = 0.27$, $p = .602$, $d = .07$ from the proportion correct on the transfer test by the groups that did not generate drawings (M = 13.3% correct, SD = 15.0). The middle portion of Table 2.2 summarizes the mean proportion correct on the retention test for the four groups. A separate ANOVA indicated that the proportion correct on the retention test by the generation groups (M = 57.8% correct, SD = 24.7) did not differ significantly, $F(1, 245) = 1.87$, $p = .172$, $d = .18$, from the proportion correct on the retention test by the groups that did not generate drawings (M = 53.6% correct, SD = 23.2). The right portion of Table 2.2 shows the mean proportion correct on the drawing test for the four groups. There was a positive main effect of generating visualizations on the drawing scores $F(1, 245) = 20.99$, $p < .001$, $d = .55$ for the biology science text, in which the groups that generated drawings (M = 55.7% correct, SD = 28.3) significantly outscored those that did not (M = 41.2% correct, SD = 24.5). There were no significant interactions.

Table 2.2
Mean Proportion Correct (Standard Deviation) on the Biology Transfer Test, Biology Retention Test, and Biology Drawing Test for all Four Groups

		Type of test					
		Transfer		Retention		Drawing	
Group	*n*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Control	59	.15	.17	.56	.25	.30	.17
Illustration	56	.11	.13	.51	.21	.53	.26
Generation	73	.16	.17	.58	.26	.51	.29
Generation + illustration	61	.13	.16	.58	.24	.62	.27

A multivariate analysis of variance (MANOVA), with generation and illustration as factors and posttest scores for chemistry and biology combined as the dependent variable, showed that there was a significant effect of generation on the posttest scores, $F(3,243) =$ 23,81, $p < .001$. Table 2.3 summarizes the mean proportion correct and standard deviations on the three posttests for the chemistry and biology science texts combined: that is, across all chemistry and biology items on the respective tests. The left portion of Table 2.3 shows the mean proportion correct and standard deviations on the transfer test for the four groups. A separate ANOVA indicated a positive main effect of generating drawings on the transfer scores for both lessons combined, $F(1, 245) = 4{,}15$, $p = .043$, $d = .28$, in which the generation groups ($M = 16.9\%$ correct , $SD = 16.0$) significantly outperformed the groups that did not generate drawings ($M = 12.9\%$ correct, $SD = 13.8$). The middle portion of Table 2.3 summarizes the mean proportion correct and the standard deviations on the retention test of both lessons together for the four groups. There was no significant main effect of generating drawings, $F(1, 245) = 1.65$, $p = .201$, $d = .17$: That is, the proportion correct for the generation groups ($M = 54.4\%$ correct, $SD = 19.9$) did not differ significantly from the groups that did not generate drawings ($M = 51.1\%$, $SD = 19.7$). The right portion of Table 2.3 shows the mean proportion correct on the drawing test in both lessons together for the four groups. There was a positive main effect of generating drawings on the drawing scores, $F(1, 245) =$ 43,54, $p < .001$, $d = .76$, in which the groups that generated drawings ($M = 47.8\%$ correct, SD $= 25.9$) significantly outscored those that did not ($M = 29.8$, $SD = 21.6$). There were no significant interactions.

Table 2.3
Mean Proportion Correct (Standard Deviation) on the Transfer Test, Retention Test, and Drawing Test for Both Lessons Combined for all Four Groups

		Type of test					
		Transfer		Retention		Drawing	
Group	*n*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Control	59	.15	.15	.54	.21	.18	.11
Illustration	56	.11	.12	.48	.18	.42	.23
Generation	73	.18	.17	.55	.20	.41	.24
Generation + illustration	61	.15	.15	.53	.19	.56	.26

Overall, there is some evidence for the generative drawing effect in computer-based learning environments. Asking students to generate computer-based drawings while reading a computer-based science text resulted in higher posttest scores on transfer and drawing, but not on retention, as compared to students who did not draw during learning. In particular, computer-based drawing during learning appears to be a generative activity, as indicated by improved transfer test performance, which is the most appropriate measure of generative processing during learning.

Do Students Report Higher Cognitive Load When They Are Asked to Generate Visualizations While Reading a Science Text?

As a validity check we examined whether students who are required to work harder by generating drawings would report higher levels of difficulty and effort. The mean difficulty ratings and standard deviations for the chemistry science text were 3.24 (SD = 1.12) for the control group, 3.60 (SD = 1.03) for the illustration group, 4.02 (SD = 1.20) for the generation group, and 3.70 (SD = 1.19) for the illustration + generation group. An ANOVA with illustration and generation as factors indicated that students' perceived difficulty in the chemistry science text was significantly higher, $F(1, 245) = 11.21$, p =.001, d = .44, for the generation groups (M = 3.92, SD = 1.24) than for the groups that did not generate drawings (M = 3.41, SD = 1.08). The mean difficulty ratings (and standard deviations) for the biology science text were 3.24 (SD = 1.24) for the control group, 3.21 (SD = 1.09) for the illustration group, 3.92 (SD = 1.57) for the generation group, and 3.50 (SD = 1.42) for the illustration + generation group. An ANOVA with illustration and generation as factors indicated that students' perceived difficulty in the biology science text was significantly higher, $F(1, 245)$ = 11.49, p = .001, d = .44, for the generation groups (M = 3.80, SD = 1.51) than for the groups that did not generate drawings (M = 3.21, SD = 1.16).

In both ANOVAs, there was no main effect of illustrations, suggesting that adding illustrations did not affect subjective reports of cognitive load. The only significant effect involving illustrations was an interaction of generation and illustrations concerning students' perceived difficulty in the chemistry science text, $F(1, 245) = 4.90$, $p = .028$, in which illustrations decreased perceived difficulty when drawing was required, but increased self-reported difficulty when no drawing was required. There were no main effects or interactions involving the effort ratings. Overall, these results suggest that generating drawings was perceived as adding difficulty to the learning task; this may be an indication of increased cognitive processing during learning.

Do Students Learn Better When They Are Asked to Generate Drawings While Reading a Science Text, When Cognitive Load is Included as Covariate?

Given the group differences in perceived difficulty—which may be an indication of cognitive load which reduces available cognitive resources for generative processing during learning (Mayer, 2009)—we reanalyzed the posttest data (posttest scores as dependent variable) using an analysis of covariance (ANCOVA), with perceived difficulty as covariate and illustration and generation as factors. The analyses yielded the same pattern of significant effects on transfer and drawing posttests as in the previous analyses and yielded additional main effects of generating visualizations on retention tests for chemistry, $F(1, 243) = 3,38$, $p = .034$, $d = .11$, biology, $F(1, 243) = 8.70$, $p = .003$, $d = .18$, and for both lessons combined, $F(1, 243) = 79.65$, $p < .001$, $d = .17$, in which students who generated drawings scored higher on retention tests than those who did not. The ANCOVA also yielded significant interactions of generation and illustration on the drawing posttest for the biology science text, $F(1, 243) = 7.29$, $p = .007$, $d = .55$ and both lessons combined, $F(1, 243) = 5.66$, $p = .048$, $d = .76$, in which the control group performed particularly poorly, as might be expected. Overall, adding the difficulty rating as a covariate served to preserve and strengthen the conclusion in the previous section, that computer-based drawing has positive effects on learning outcomes.

Do Students Need More Study Time When They Are Asked to Generate Visualizations While Reading a Science Text?

As a further validity check we examined whether students who are required to generate drawings need more time to study the science lessons. A multivariate analysis of variance (MANOVA) with generation and illustration as factors and study time for the chemistry and biology science text as the dependent variables showed that there was a significant effect of generation on study time, $F(2,195) = 142,13$, $p <.001$. The mean study time (and standard deviations) for the chemistry science text were: 10.60 min ($SD = 3.02$) for the control group, 10.99 min ($SD = 2.61$) for the illustration group, 24.98 min ($SD = 9.08$) for the generation group, and 23.25 min (*SD* = 7.04) for the illustration + generation group. A separate ANOVA[2] with illustration and generation as factors indicated that students' study time in the chemistry science text was significantly higher, $F(1, 196) = 201{,}81$, $p <.001$, $d = .22$, for the generation groups ($M = 24.2$ min, $SD = 8.26$) than for the groups that did not generate drawings ($M = 10.8$ min, $SD = 2.84$). The mean study time (and standard deviations) for the biology science text were: 10.76 min ($SD = 3.12$) for the control group, 10.80 min ($SD = 2.52$) for the illustration group, 23.51 min ($SD = 7.26$) for the generation group, and 20.45 min ($SD = 5.43$) for the illustration + generation group. A separate ANOVA with illustration and generation as factors indicated that students' study time for the biology science text was significantly higher, $F(1, 196) = 216{,}60$, $p< .001$, $d = .22$, for the generation groups ($M = 22.2$ min, $SD = 6.67$) than for the groups that did not generate drawings ($M = 10.8$ min, $SD = 2.86$). There were no other significant effects or interactions. Overall, as might be expected, asking students to draw illustrations added substantially to study time, so the benefits of computer-based drawing should be weighed against the cost of additional study time.

Is the Quality of Drawing During Learning Related to Better Learning Outcomes?

The foregoing sections provided evidence for a generative drawing effect, in which asking students to create computer-based drawings of science text during learning resulted in improved posttest performance. In the present analysis, we focus on the quality of the drawings produced by students in the drawing groups, in order to determine whether the quality of student drawings during learning is related to posttest performance. According to the prognostic drawing principle established with hand-drawn student drawings (Schwamborn et al., 2010), we would expect the quality of computer-based drawings produced during learning to be positively related to posttest scores on transfer, retention, and drawing.

As a first step in testing the prognostic drawing principle, we pooled the two generation groups, because their scores on drawing accuracy during learning did not differ significantly for the chemistry science text, $F(1, 122) = 1.13$, $p = .289$, $d = .19$, and for the biology science text, $F(1, 122) = 0.87$, $p = .352$, $d = .19$.

Second, correlation analyses based on the combined data from the two generation groups revealed that the proportion correct in computer-based drawings (i.e., accuracy score) that students produced during chemistry learning correlated significantly with each of the three posttest measures for the chemistry science text: transfer test, $r = .51$, $p < .01$; retention test, $r = .41$, $p < .01$; and drawing test, $r = .52$, $p < .01$. Correlation analyses based on the

[2] Because of missing log-files concerning study time, degrees of freedom vary.

combined data from the two generation groups revealed that the accuracy score of drawings that students produced during learning with the biology science text correlated significantly with each of the three posttest measures for the biology science text: transfer test, $r = .54$, $p < .01$; retention test, $r = .58$, $p < .01$; and drawing test, $r = .64$, $p < .01$. This pattern of results shows a strong positive relation between the quality of students' generated drawings during learning and their performance on the posttests. This is the primary evidence in support of the prognostic drawing effect, which states that the quality of drawings during learning predicts the quality of posttest performance on measures of learning outcome.

Third, as shown in Table 2.4, we classified each student in the two generation groups as a high-accuracy drawer or a low-accuracy drawer on the basis of a median split of the drawing accuracy score of the chemistry drawings generated during the chemistry science text. The mean proportion correct was 45.98% ($SD = 29.66$) for the high-accuracy visualization generators and 13.83% ($SD = 8.76$) for the low-accuracy visualization generators, $t(128) = 15.70$, $p < .001$, $d = 1.47$. T-tests revealed that the high-accuracy drawers significantly outperformed low-accuracy drawers on each of the posttest scores on the chemistry science text: transfer test, $t(128) = 17.93$, $p < .001$, $d = .98$; retention test, $t(128) = 0.93$, $p < .001$, $d = .67$; and drawing test, $t(128) = 0.50$, $p < .001$, $d = 1.08$.

Table 2.4
Mean Proportion Correct (Standard Deviation) on the Chemistry Transfer Test, Chemistry Retention Test, and Chemistry Drawing Test by Low- and High-Accuracy Drawers From Both Generation Groups Combined

		Type of test					
		Transfer		Retention		Drawing	
Group	*n*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Low-accuracy drawers	66	.11	.14	.44	.20	.26	.25
High-accuracy drawers	64	.28	.20	.58	.22	.54	.27

Similarly, Table 2.5 shows each student in the two generation groups classified as a high-accuracy drawer or a low-accuracy drawer, on the basis of a median split of the accuracy score of the drawings generated during the biology science text. The mean proportion correct was 67.21% ($SD = 17.46$) for the high-accuracy drawers and 19.25% ($SD = 11.69$) for the low-accuracy drawers, $t(126) = 15.20$, $p < .001$, $d = 3.23$. T-tests revealed that the high-accuracy drawers significantly outperformed low-accuracy drawers on each of the posttest scores for the biology science text: transfer test, $t(126) = 31.24$, $p < .001$, $d = 1.03$; retention test, $t(126) = 0.34$, $p < .001$, $d = 1.19$; and drawing test, $t(126) = 0.65$, $p < .001$, $d = 1.36$. These findings provide strong and consistent support for the prognostic drawing principle.

Table 2.5
Mean Proportion Correct (Standard Deviation) on the Biology Transfer Test, Biology Retention Test, and Biology Drawing Test by Low- and High-Accuracy Drawers From Both Generation Groups Combined

		Type of test					
		Transfer		Retention		Drawing	
Group	*n*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Low-accuracy drawers	64	.07	.10	.45	.20	.40	.25
High-accuracy drawers	64	.22	.18	.70	.22	.72	.22

Do Students Learn Better When They Receive Instructor-Provided Illustrations While Reading a Science Text?

In addition to the analyses described above, we were interested in whether there was evidence for the multimedia effect (Fletcher & Tobias, 2005; Mayer, 2009), which states that students learn better from lessons containing text and illustrations than from text alone. According to this effect, and to findings from Schwamborn et al. (2011; see also Schmeck, 2010), we expected students provided with illustrations to perform better than students who were not given illustrations in their lessons.

Table 2.1 summarizes the mean proportion correct and the standard deviations for the chemistry science text on each of the three posttests. An ANOVA indicated no main effect of presenting illustrations on the transfer scores, $F(1, 245) = 1.79$, $p = .182$, $d = -0.18$. There was a significant negative main effect of presenting illustrations on the retention scores, $F(1, 245) = 4.13$, $p = .043$, $d = -0.26$, in which students who received instructor-generated illustrations (M = 46.9% correct, SD = 22.8) performed significantly worse than those who did not (M = 52.6% correct, SD = 21.5). There also was a significant negative main effect of presenting illustrations to the students on the drawing scores, $F(1, 245) = 57.63$, $p < .001$, $d = 0.84$, in which students who received instructor-generated illustrations (M = 42.1% correct, SD = 31.5) performed significantly worse than those who did not (M = 19.1% correct, SD = 22.2).

Table 2.2 summarizes the mean proportion correct for the biology science text. An ANOVA indicated no main effect of presenting illustrations on the transfer scores, $F(1, 245) = 2.61$, $p = .108$, $d = -0.21$. Another ANOVA indicated no main effect of presenting illustrations on the retention scores $F < 1$. For the biology science text, there was a positive main effect on the drawing scores from providing illustrations while reading, $F(1, 245) = 26.69$, $p < .001$, $d = .59$, wherein students who received instructor-generated illustrations (M =

57.3% correct, $SD = 26.7$) significantly outperformed those who did not ($M = 41.6\%$ correct, $SD = 26.2$).

Table 2.3 summarizes the mean proportion correct for the chemistry and the biology science texts combined. An ANOVA indicated no main effect of presenting illustrations on the transfer scores, $F(1, 245) = 2.69$, $p = .102$, $d = -0.22$. Another ANOVA indicated no main effect of presenting illustrations on the retention scores on both lessons combined, $F(1,245) = 3.04$, $p = .083$, $d = - 0.23$. There was a positive main effect on the drawing scores from giving illustrations while reading $F(1, 245) = 52.88$, $p < .001$, $d = .81$, for the chemistry and biology science texts combined, in which students who received instructor-generated illustrations ($M = 49.7\%$ correct, $SD = 25.6$) significantly outperformed those who did not ($M = 30.4\%$ correct, $SD = 22.0$).

Overall, the small and inconsistent effect sizes on retention and transfer do not support the multimedia effect in this study. As already mentioned above, there were no significant interaction effects, meaning that the effect of the provided illustrations is not moderated by the generation of visualizations.

2.7 Discussion

Empirical Contributions

The main empirical contribution of this study is that students learned better when they generated computer-based drawings while reading onscreen science texts. Thus, the results show that the generative drawing effect extends to a computer-based learning environment (where appropriate instructions and pretraining are given on using the drawing tool). The second empirical contribution of this study is that students who produced high-accuracy drawings on a computer while reading science texts scored better on learning outcome posttests than students who produced low-accuracy drawings on a computer while reading. Thus, the results show that the prognostic drawing effect extends to a computer-based learning environment.

Theoretical Contributions

The results are consistent with generative theories of learning (Mayer, 2009), which posit that people learn better when they engage in generative processing during learning, that is, cognitive activities aimed at making sense of the material. Generating computer-based drawings while reading is intended to cause students to translate the verbal information into a visualization that expresses the relevant relationships between the elements referred to in the text, leading to a connection of verbal information, visual information, and prior knowledge. This generative cognitive processing leads to deeper understanding according to the CTML (Mayer, 2009) and CLT (Sweller, Ayres, & Kalyuga, 2011). These intended generative cognitive processes can be impaired or even impeded by extraneous cognitive load caused by the mechanics of using a tedious interface to create onscreen drawings, leading to insufficient cognitive resources being available for generative processing. Thus, in the present study we tried to create a form of visualization generation that minimized extraneous processing by providing a ready-made drawing background and a toolbar with all the relevant elements that could be dragged and dropped onto the background, along with appropriate pretraining.

Overall, the results show that asking learners to generate drawings of scientific texts, using a computer-based tool, fosters generative processing. Thus, this study is in line with earlier studies, reviewed in the introduction, showing the generative drawing effect when instructional support is given during students' process of drawing by hand on paper.

The results show that the instructional support given during the drawing process within the computer-based learning environment seamed to be sufficient to foster generative processing, while minimizing extraneous processing caused by the mechanics of the drawing interface. On the transfer learning outcome tests, which are the most appropriate measures of generative processing during learning (Mayer, 2009), students who generated drawings outperformed the students who did not. Thus, computer-based drawing during learning appears to be a generative activity. However, group differences were found concerning the perceived difficulty, suggesting that generating drawings was perceived as adding difficulty to learning tasks; this also is in line with earlier studies, e.g., Leutner et al. (2009), Schwamborn et al. (2011). Adding difficulty ratings as a covariate strengthened the finding of a positive effect of computer-based drawing on learning, by showing stronger effect sizes.

Results concerning study time show significant group differences which indicated that students' study time was higher for the generation groups than for the groups that did not generate drawings within the chemistry as well as in the biology learning environment. This was in line with the assumption, that students learning with self-generated drawings have to use drawing mechanics to build up an external model, i.e., drawing, besides the cognitive processing of selecting, organizing and integrating, to build up a coherent mental model of the to be learned information. This process of course takes up time by itself. Additionally, the effects of generating drawings on the transfer test scores were in line with the results of Schwamborn, Thillmann, et al. (2010), who also used self-paced study time. When using self-generated drawing students need to conduct cognitive and metacognitive processing of the information as well as mechanical processing of drawing suitable, to achieve an ideal learning outcome (van Meter & Garner, 2005). Although, a causal interpretation is still not possible, without more empirical studies, it seems that a sufficient study time can counteract the higher cognitive load caused by the drawing mechanics within this learning strategy. As a result self-generated drawing can then be effective (Leutner et al., 2009; Sweller, 2005). Looking at the averaged study time within the generation groups, self-generated drawing proved to be a relative efficient learning strategy.

Additionally, our results are again in line with the theory of generative drawing (van Meter, 2001, 2005), which states that students who engage effectively in generating visualizations tend to build up a more coherent idea of the learning content and therefore construct meaningful learning outcomes also. Thus, the accuracy of the visualizations reflects the quality of the generative process during learning and is related to learning outcome measures of retention, transfer and drawing scores. Overall, the diagnostic value of the drawing accuracy scores is reflected in the finding that students who produced higher-accuracy drawings during learning tended to score higher on learning outcome posttests.

Practical Contributions

Based on the present results, we propose a generative drawing principle in computer-based learning environments, in which students learn better when they generate drawings by means of drag-and-drop on the computer screen while learning from an onscreen science text. Nevertheless, it is important to implement the drawing process through a method that reduces extraneous processing initiated by the mechanics of drawing. That is why we used the earlier-described drawing interface and the drag-and-drop mechanism as a support for drawing. Based on the present findings, we recommend asking students to draw computer-based drawings during computer-based learning with science texts.

Additionally, we propose the prognostic drawing principle for computer-based learning: The accuracy of the visualizations students draw during learning predicts the quality of learning outcomes. The students' generated drawings give some indication of their level of understanding of the text content. On the one hand, students could use the accuracy of their generated visualizations to monitor what they have understood, and could go back to the text if necessary. On the other hand, teachers could use drawing accuracy to assess learning and adjust their instruction accordingly. It is possible that drawing accuracy offers more, or at least different information about students' level of understanding than students can describe verbally. Thus, both principles are important for school practice, most of all because they extend to computer-based learning environments, which have gained increasing attention and importance within educational contexts in recent years.

Limitations and Future Directions

The present study was limited in some areas that should be investigated in future studies. In addition to the results reported so far, we did not find an effect of the order of the offered lesson: That is, the order in which the students undertook the particular science lesson (chemistry or biology) did not effect their performance in posttests. Additionally, this seems to show that there was no effect of previous learning on later learning, which was expected due to suggestions of Schmeck (2010) based on results of Kellogg and Mueller (1993) who showed that students trained in using a strategy perform better. Further research is needed to see if computer-based drawing can improve learning over time.

As mentioned above, we found only small and inconsistent effect sizes of presenting illustrations on retention and transfer, which consequently do not support the multimedia effect in this study. Additionally, there were no significant interaction effects concerning providing illustrations and generating drawings; this means that the effect of the provided illustrations was not moderated by the generation of drawings. One possible explanation is that the learners did not pay much attention to the computer-based illustrations. This possibility is consistent with our finding that students did not spend more study time on lessons containing illustrations than on lessons that did not contain illustrations.

Because of the significant difference, concerning perceived difficulty, between students who generated visualizations and those who did not, it might be suggested that despite the drawing support (which seems to have been successful in comparison to previous computer-based studies) the drawing procedure based on drag-and-drop, is still a bit too intrusive for some students. One possible explanation for this could be that this procedure is still not the same as using a pencil, which in general is a familiar learning procedure for students. Future work is needed to determine if we can strengthen the effects of the generative drawing principle within computer-based learning environments by using a form of drawing mechanism that is more natural and that students are used to, so that it minimizes extraneous processing. In particular, it would be useful to incorporate a tablet computer in the learning environment, which would allow the students to use a pencil but still work with computers as a medium. Additionally, the use of tablet computers could help support students' creativity. Their creativity was restricted in this study, due to the provision of a partially drawn background and of the elements the students were required to use. Perhaps the greater freedom in drawing, which students have when they work with paper and pencil, could better support their learning, although it could, on the other hand, become a source of extraneous processing for inexperienced learners. Thus, further research concerning the role and the degree of guidance needed for self-generated drawings in computer-based learning environments would assist in developing more efficient and supportive learning environments.

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3 Study II: Generative Drawing – Differences in Using Paper-Based Material and Drawing by Hand Versus Using Computer-Based Material and Drawing by Drag-and-Drop

Abstract

Generative drawing is a learning strategy to foster deeper student learning. Using this strategy, students are asked to create drawings as they read a scientific text. However, researchers have noted that students report difficulties when they draw via computer rather than by hand. The present study examined the contrast between drawing by hand versus drawing by computer. Fifty-four 8^{th} graders read a 6-paragraph text dealing with chemistry in which paragraphs were alternately presented on paper (with instructions to create a drawing by hand) and on a computer screen (with instructions to use a drag-and-drop interface to create a drawing). This was followed by a posttest of retention learning outcome. A repeated measures ANOVA with the presentation medium (computer- and paper-based) as within-subjects factor was performed. Results showed that students learn significantly more when they read and generate drawings on paper than on a computer screen. Perceived difficulty was measured after every text paragraph. Results revealed that students reported significantly less perceived difficulty when working with a text-paragraph in the computer-based learning environment than in the paper-based learning environment. On a subsequent questionnaire, students generally reported fewer difficulties when generating drawings by drag-and-drop on the computer. Additionally, they reported a higher level of motivation when using the computer for generating. Finally, the prognostic drawing principle is supported in paper-based as well as in computer-based learning environments. Importantly, results concerning the questionnaire provide information to improve learning environments concerning generative drawing in the future.

Keywords: computer-based learning, paper-based learning, generative drawing, cognitive load, motivation

3.1 Theoretical Background

Within their school career, students need to learn a lot of scientific phenomena. These phenomena are usually complex and cannot be observed directly. Research has shown that students have difficulties in understanding scientific concepts (Driver, Leach, Scott, & Wood-Robinson, 1994). To make it easier for students, many teachers use experiments or animations. Experiments and animations can be presented on various media, such as on a computer screen, as physical experiments, or printed on paper. When the information to be learned, from text and/or visual representations, is presented on a computer screen, this kind of learning environment is categorized as computer-based learning environment. Using computers and other 'new media' presents numerous possibilities of how to share information with an audience and, not surprisingly, learning with new media has become a common research topic in educational psychology. This started in the sixties when new media – that is, electronic, digital and interactive media – were increasingly developed and distributed (Zander & Brünken, 2006). Looking at learning with real (Hofstein & Lunetta, 2004) and virtual (Chen, 2010) experiments, results showed positive effects of both on students' learning outcome. The same applies to learning with animations, including highly realistic video-based animations (e.g., Michas & Berry, 2000; Spangenberg, 1973) and computer-based animations (e.g., Höffler & Leutner, 2007; Imhof, Scheiter, Edelmann, & Gerjets, 2012). However, using scientific texts as learning material is still unavoidable in everyday school life, and these can be presented on a computer as well as on paper. Often, when students need to learn from scientific texts, they find the complexity of these texts difficult and thus are sometimes unable to cope with the cognitively highly demanding process of comprehension (Naumann, Artelt, Schneider, & Stanat, 2009).

An alternative to text-only presentations is to use multimedia presentation, in which students learn from both text and pictures (Mayer, 2009; Schnotz, 2005; Schnotz & Bannert, 1999). Learning with multimedia presentations has been shown to be effective in paper-based learning environments (e.g., Mayer, 1989; Mayer & Anderson, 1991, 1992; Mayer & Gallini, 1990; Moreno & Mayer, 1999; Plass, Chun, Mayer, & Leutner, 1998; Schwamborn, Thillmann, Leopold, Sumfleth, & Leutner, 2010) as well as in computer-based learning environments (e.g., Brünken, Steinbacher, Schnotz, & Leutner 2001; Mayer & Moreno, 2002; Schmidt-Weigand, 2006; Schwamborn, Mayer, Thillmann, Leopold, & Leutner, 2010). The research mentioned above has used pictures to foster students' learning process when reading scientific texts. Another approach to foster this learning is to ask students to draw a picture during reading concerning the content presented in the text. Drawing is a learning strategy that improves students' text comprehension by enhancing active cognitive and metacognitive processing (Alesandrini, 1984; Schmeck, 2010; Schwamborn, Thillmann, et al., 2010; van Meter & Garner, 2005). Accordingly, the generative theory of drawing construction by van Meter and Garner (2005) states that students who are asked to generate a picture while reading a text engage in three different cognitive processes. The first process is the selection of important elements from the verbal representation, i.e., the text. The second cognitive process is organization, whereby the selected elements are used to build up an internal verbal model, which under integration of existing prior knowledge serves as the basis for constructing an internal nonverbal representation. Thereby, the organization of the verbal representation guides the organization of the nonverbal representation. Additionally, students integrate this internal nonverbal representation with the verbal model. According to van Meter and Garner (2005), the process of integrating verbal and nonverbal representations is not distinct from the process of organizing nonverbal representations. Instead, the organized verbal representation is the basis for the nonverbal representation both are necessarily integrated. Learners are literally forced to integrate both when generating an external nonverbal representation. This third cognitive process, integration, allows the student to be able to generate an external nonverbal representation, for example, a visualisation representing all relevant content of the learned text. That is, when students draw during reading, the organized verbal representation is used to construct the nonverbal representation. Specifically, when the introduced concepts are new for the student and no prior knowledge is available to refer to, the organized verbal representation is used to construct the nonverbal representation when students draw during reading. Through this process of generating (referential) connections between all representations described here students build up a mental model, which is assumed to be the reason for enhanced problem solving abilities (e.g., Mayer & Gallini, 1990; Mayer & Sims, 1994; van Meter & Firetto, 2013; van Meter & Garner, 2005) and therefore enhanced learning outcome.

In addition to enhanced active cognitive processing, like selection, organization and integration, drawing also increases active processing on a metacognitive level (van Meter & Garner, 2005). At a metacognitive level, the cognitive process of drawing is not necessarily linear (van Meter & Garner, 2005). Sometimes when students try to draw a picture, they encounter problems: Perhaps they do not understand all of the text or they do not know how to draw elements described in the text and where to place them to show relationships correctly. Students then need to go back to their internal nonverbal and/or the verbal representation or even back to the text itself to be able to continue drawing. Thus, they monitor and regulate themselves during learning with drawings (Leopold, 2009; Leopold & Leutner, 2015; van Meter, 2001). In other words, instructing students to draw a picture representing the relevant text information can enhance metacognitive processes.

The activation of cognitive and metacognitive processes by drawing also corresponds to the 'generative processing' assumed in the Cognitive Theory of Multimedia Learning (CTML; Mayer, 2009) as well as to 'germane cognitive load' defined in Cognitive Load Theory (CLT; Chandler & Sweller, 1991; Sweller, Ayres, & Kalyuga, 2011). Following the Cognitive Theory of Multimedia Learning and Cognitive Load Theory, the process of drawing while reading a scientific text does not only foster generative processing (respectively germane load), but also extraneous processing (respectively extraneous cognitive load; Chandler & Sweller, 1991; Leutner, Leopold, & Sumfleth, 2009; Mayer, 2009; Sweller et al., 2011). Translating printed text into a pictorial representation, such as when learners are asked to generate drawings, can prime germane load (respectively generative processing), which is the effort that contributes to the construction of schemas (Sweller, Merrienboer, & Paas, 1998), by selecting important material, organizing it into a coherent structure, and integrating it with relevant prior knowledge. However, on the other hand, instructing students to draw does not automatically guarantee generative processing and thus a better understanding of the text. The mechanics of drawing, both on paper and on a computer-screen, can be difficult and therefore can create extraneous load. If the drawing process itself creates too much extraneous load, there will be not enough cognitive resources available in working memory for germane load; thus learning is impaired (Sweller, 2010).

State of Research Concerning Generative Drawing

Research so far has shown that learning from paper-based texts can be improved when students engage in hand drawing using paper and pencil (Leopold, 2009; Leopold & Leutner, 2012; Schmeck, 2010; Schwamborn, Mayer et al., 2010; Schwamborn, Thillmann et al., 2010; van Meter & Garner, 2005; see also van Meter, 2001). However, studies on generative drawing that did not include instructional support during the drawing process often did not show an improvement in learning performance (Leutner et al., 2009; Rasco, Tennyson, & Boutwell, 1975; Tirre, Manelis, & Leicht, 1979), whereas studies with support did foster text comprehension (Study I of this thesis; Lesgold, Levin, Shimron, and Gullman, 1975; Lesgold, De Good, & Levin, 1977; Schwamborn, Mayer et al., 2010; Schwamborn, Thillmann et al., 2010; van Meter, 2001; van Meter & Garner, 2005; van Meter, Aleksic, Schwartz, & Garner, 2006). Accordingly, Schwamborn, Mayer, and colleagues (2010) proposed the *generative drawing principle*, which states that students learn better from science texts – only if the drawing activity is implemented in a way that minimizes extraneous cognitive load. Additionally, Schwamborn, Mayer, et al. (2010) introduced the *prognostic drawing effect*, in which the accuracy score of student-generated drawings during learning correlates positively with posttest scores.

All of these presented effects refer to studies that dealt with hand drawing using paper and pencil. But what about cases in which science texts are presented on a computer screen and students need to engage in drawing by using the mechanics of drag-and-drop? In the first study (Schwamborn, Thillmann, Opfermann, & Leutner, 2011) that investigated the effects of computer-based generative drawing, students were instructed to draw their pictures on a computer screen by means of drag-and-drop. Results of this study showed that students who drew on the computer screen performed better on a drawing test than students who learned with provided pictures or the control group. However, there were no significant effects on transfer and retention tests and thus results were not in line with generative theories (de Jong 2005; van Meter & Garner, 2005; Wittrock, 1990). Additionally, Schwamborn and her colleagues (2011) found that using a computer-based learning environment seems to demand too much extraneous cognitive load meaning that students reported increased mental effort while learning with the computer-based drawing material. These students also needed more learning time than the non-generating groups.

In the second study that investigated the effects of computer-based generative drawing (see Study I in Chapter 2 of this thesis), students were again instructed to draw their pictures on a computer screen by means of given elements and drag-and-drop. However, in this study learning material was taken from Schwamborn et al. (2011) and it was adapted to improve it for computer-based learning. Additionally, a second learning content was taken from Schmeck, Mayer, Opfermann, Pfeiffer, and Leutner (2014) and programmed to make it also suitable for computer-based learning. The second content was used, on the one hand, to clarify that the specific learning content was not the reason that no benefits of computer-based generative drawing were found in the first study (Schwamborn et al., 2011). On the other hand, a second content also helps students to get acquainted with the computer-based learning environment. The use of a second learning content combined with training tutorials and an optimized handling of the learning material should decrease extraneous cognitive load and thus leaving more cognitive resources available for generative processing and meaningful learning (Mayer, 2009). In Study I of this thesis (Chapter 2), we did assume that these alterations and arrangements should increase the positive effects of computer-based generative drawing on students' learning outcome.

In contrast to the study of Schwamborn et al. (2011), Study I showed that learning from a science text presented on a computer-screen improves performance on learning outcome posttests when students engage in drawing using drag-and-drop. Students learned better when they generated computer-based drawings while reading onscreen science texts. Thus, the results showed that the generative drawing effect extends to a computer-based learning environment if appropriate instructions and pretraining on using the drawing tool are given. Additionally, results showed that the prognostic drawing effect (Schwamborn, Mayer, et al., 2010) extends to this computer-based learning environment, as students who produced high-accuracy drawings on a computer while reading science texts scored better on learning outcome posttests than students who produced low-accuracy drawings.

However, this study also indicated, as in the study of Schwamborn and colleagues (2011), that using a computer-based learning environment seems to demand too much extraneous cognitive load, meaning that students here reported an increased perceived difficulty when generating drawings. According to these studies, asking students to use generative drawing runs the risk of creating too much extraneous cognitive load. This can lead to fewer cognitive resources being available for generative processing, respectively germane cognitive load, that is needed for deep-level understanding (Mayer, 2009).

Overall, comparing results from previous studies concerning paper-based generative drawing with computer-based drawing studies, it strikes us that one computer-based drawing study did not find support for the benefits of generative drawing (Schwamborn et al., 2011), whereas the other computer-based drawing study (our Study I, Chapter 2) showed positive effects of generative drawing on learning outcome. However, our Study I still revealed smaller effect sizes than studies using paper-based learning material (cf. Schwamborn, Mayer et al., 2010; Schwamborn, Thillmann et al., 2010; Schmeck, 2010; Schmeck et al., 2014). These inconsistenties are the motivation for the present study.

Outline of the Present Study and Hypothesis

To our knowledge, only two studies have investigated generative drawing on a computer screen by means of drag-and-drop (Study I, Chapter 2; Schwamborn, et al., 2011), and there is no published study that directly compared paper-based generative drawing with computer-based generative drawing. In the present study we intend to investigate the inconsistency concerning the effect of generative drawing in paper-based and in computer-based learning environments. We do this by instructing students to use the generative drawing strategy on paper as well as on the computer, with students alternately reading science texts on paper and on the computer screen. Thus, the generative drawing medium is a within-subjects-factor in our study. We measure students' learning outcome of science content learned on paper and on the computer to compare the effectiveness of computer- and paper-based generative drawing. We also investigate which medium (and therefore which mechanics) students perceive to be more difficult to work with, that is, which causes more extraneous cognitive load. Additionally, we look at the prognostic drawing principle in the paper-based as well as in the computer-based parts of the lesson. That is, we investigate whether the accuracy of student-generated drawings during learning correlates positively with posttest scores for both parts of the lesson. Finally, we also want to explore the underlying components of students' perceived task difficulty. Thus, we examine possible explanations for differences in the effectiveness of the generative drawing principle based on whether students draw by hand or draw on the computer using drag-and-drop (Schwamborn, Mayer et al., 2010; Schmeck et al., 2010; see Study I, Chapter 2). In doing so, we will try to provide recommendations on how to successfully integrate generative drawing in the instructional context. In sum, we intend to investigate the following hypotheses: First, concerning learning outcome we assume that students will perform better on those learning outcome questions whose content was learned in the paper-based learning environment than on those whose content was learned in the computer-based learning environment. This is due to the assumption that the extraneous load is expected to be lower for the paper-based learning environment. Second, we assume that students perceive a higher difficulty when working in the computer-based learning environment than when working in the paper-based learning environment. Third, we predict that the accuracy of the learners' drawings made during learning with both types of material will predict performance on the posttests. We predict that the accuracy of drawings made in the paper-based parts of the lesson will at least predict performance on the learning outcome of content learned with the paper material, but presumably also concerning content learned with the computer-based material. We predict that the same applies for the accuracy of the drawings made in the computer-based parts of the lesson. The assumption of the prognostic drawing principle also means that students with a high accuracy score are expected to perform better on learning outcome scores than students with a low accuracy score. Finally, we assume that students experience various kinds of difficulties when using a computer-based or paper-based approach to generate drawings during learning from a science text. These could be difficulties to learn the important content from the material, difficulties with the mechanics of the drawing process itself, or difficulties to be motivated by one or the other learning material. In this study we are interested in these differences, and we investigate what is easier or more difficult in computer-based and in paper-based approaches, in order to create an easy-to-use and effective way to implement generative drawing in the long run.

3.2 Method

Participants and Design

In this study participants were 54 German 8th graders from higher track secondary schools. Their mean age was 13.4 (SD = 0.7), and 57.4% were female. All 54 participants were presented with a chemistry science text and completed the posttest. Within their classes, students were randomly assigned to one of two sequence groups: 27 students began with paragraph one of the chemistry science text on the computer then switched to paper for the second paragraph, then on the computer, and so on (the ‘Computer-Paper Sequence Group’). The other 27 students began with paragraph one of the chemistry science text on paper then switched to the computer for the second paragraph and so on (the ‘Paper-Computer Sequence Group’). Thus, all students received the whole 6-paragraph chemistry science text with the medium (paper, computer) changing for each successive paragraph (exemplified in Table 3.1).

Table 3.1
Sequence in Which the Students Were Provided With the Paper-Based and Computer-Based Learning Material and the Remaining Procedure of the Experiment, Depending on Their Group

	‘Computer-Paper Sequence’ Group’	‘Paper-Computer Sequence’ Group’
Training 1	Paper	Computer
Training 2	Computer	Paper
Paragraph 1	Computer	Paper
	Perceived Difficulty Item	
Paragraph 2	Paper	Computer
	Perceived Difficulty Item	
Paragraph 3	Computer	Paper
	Perceived Difficulty Item	
Paragraph 4	Paper	Computer
	Perceived Difficulty Item	
Paragraph 5	Computer	Paper
	Perceived Difficulty Item	
Paragraph 6	Paper	Computer
	Learning Outcome Test	

Materials and Apparatus

We adapted the learning material from the chemistry science text of Schwamborn, Thillmann, et al. (2010), which we also used in our Study I (see Chapter 2). The computer-based materials consisted of a chemistry text of approximately 1000 words dealing with the chemistry of washing with soap and its influence on the water surface tension. The lesson consisted of six pages, each containing one paragraph about the causal steps in the process of mixing soap and water. In the computer-based materials, the text paragraphs were augmented with a drawing prompt, which included (1) a toolbar showing all relevant pictorial elements, as well as a tooltip with the names of the elements as described in the science text in case of mouse over, (the pictorial elements could be moved, rotated, and combined on the screen by means of drag-and-drop) and (2) a partly pre-drawn background onto which elements could be placed (exemplified in Figure 3.1). Additionally, there was a computer-based pre-training whose setup was the same as of the computer-based chemistry science text. However, within this first exercise students were instructed to generate an easy drawing of a little man on the partly pre-drawn background by means of given elements from the toolbar, using drag-and-drop.

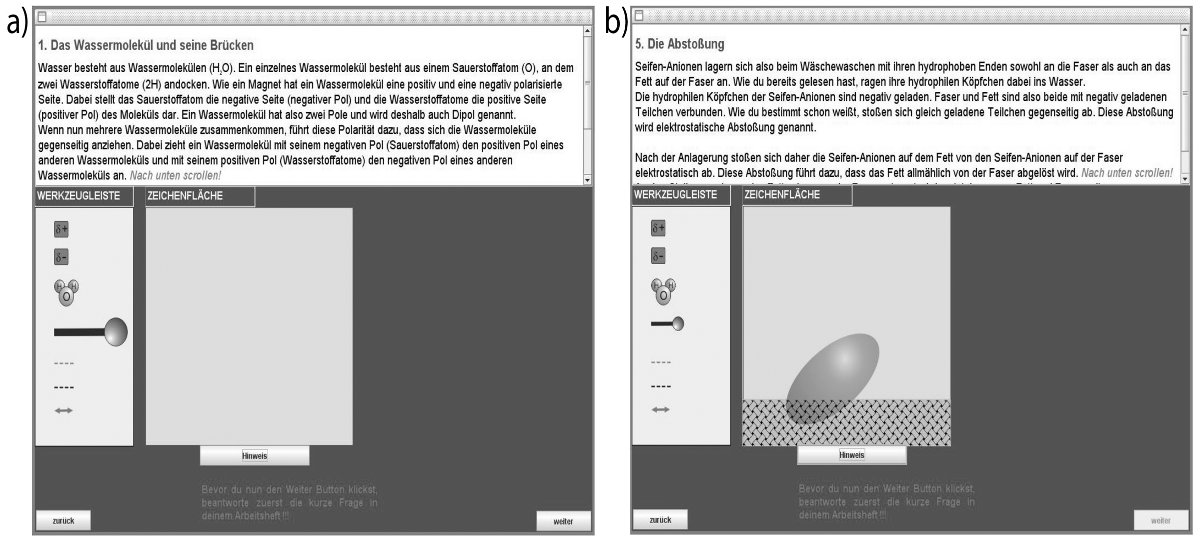

Figure 3.1 Two example frames of the computer-based chemistry learning material for (a) paragraph one and (b) for paragraph five (German version).

The computer apparatus consisted of 35 Dell computer systems on which the learning environment was installed.

The paper-based materials consisted of a learning booklet that included the same chemistry science text as the computer-based materials. The setup of the lesson followed the setup of the computer material with the printed science text paragraph on the top of each page, augmented with a drawing prompt on the bottom. This drawing prompt also included two parts. (1) A printed toolbar (on the left side) that showed the various elements and their names as described in the science text for generating drawings for the respective text paragraph. However, in this case, students had to select and combine the given elements and then re-draw them by hand onto (2) a pre-printed background (on the right side). The paper-based lesson is exemplified in Figure 3.2. Additionally, there was also a paper-based pre-training whose setup was the same as of the computer-based chemistry science text, but the students were instructed to generate an easy drawing of a little man on the pre-drawn background by means of given elements from the toolbar on paper.

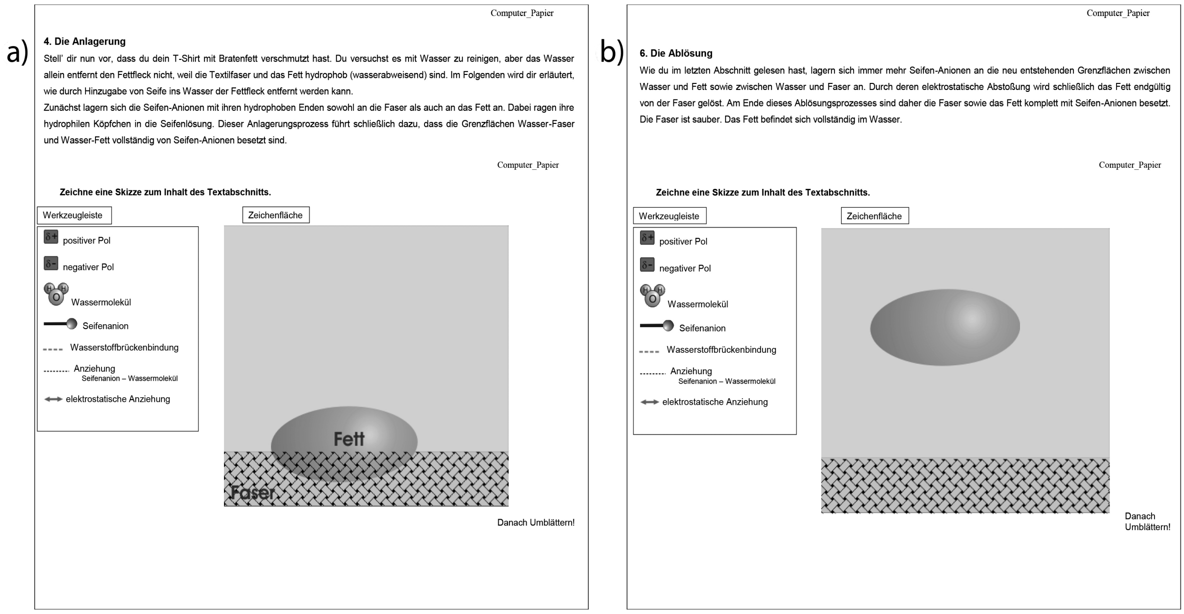

Figure 3.2 Two example frames of the paper-based chemistry learning material for (a) paragraph four and (b) for paragraph six (German version).

The learning booklet additionally comprised the same item six times asking the students about their perceived difficulty experienced during learning with the previous paragraph. This was assessed online, meaning immediately and continuously one item after each paragraph, asking the learners to rate the perceived task difficulty on a 7-point scale based on the item of Kalyuga, Chandler, and Sweller (1999). Our modified item (translated) was: “How difficult was it for you to generate a drawing for the previous text paragraph?”. Responses ranged from (1) ‘very easy’ to (7) ‘very difficult’. The booklet also included hints to turn over the page and to work with the next paragraph on the computer or on paper to support and instruct the students in their working process.

Further paper-based materials were a participant questionnaire, a spatial ability pretest, a ‘Medium Preference Questionnaire’ and a learning outcome posttest. The participant questionnaire solicited demographic information, students’ performance grade in school chemistry, and an estimate of their computer usage. For the spatial ability pretest, the Card Rotation Test (CRT; Ekstrom, French, & Harman, 1976), consisting of ten items, was used. We developed the Medium Preference Questionnaire because we could not find a published questionnaire concerning deeper insight into perceived difficulty. The questionnaire had 13 items and measured students' preference for learning medium on three separate components. This taxonomie was composed to represent all relevant steps and mechanics students undergo when generating drawings and to differentiate possible difficulties students might try to express when they are asked how difficult a learning unit was for them. By means of this questionnaire we wanted to be able to look at the differences between the learning media in detail. The components were based on issues with the learning material media that our research team gathered from a small pilot study and on difficulties students reported to the experimenters after they had learned with the computer-based material of Study I. The first component was *enthusiasm* (2 items), which tapped into students' enjoyment while generating drawings. An example item (translated) is: "Drawing the pictures was... (1) strikingly more fun on the computer, (2) a little more fun on the computer, (3) a little more fun on paper, or (4) strikingly more fun on paper". The second component was *difficulties with the mechanics* of the drawing process (6 items), which concerned problems students had while drawing. An example item is: "For me, orienting the drawing elements on the drawing background was… (1) strikingly easier on the computer, (2) a little easier on the computer, (3) a little easier on paper, or (4) strikingly easier on paper". The third component was *metacognition and learning* (5 items) and referred to processes like self-regulation as well as understanding of the learning content. An example item is: "For me, understanding the contents of the text paragraphs was… (1) strikingly easier on the computer, (2) a little easier on the computer, (3) a little easier on paper, or (4) strikingly easier on paper". All items are listed in Table 3.4 in the results part of this study, each with 4-point Likert-type response scale.

The learning outcome posttest was a retention test consisting of six open-ended questions, each related to one of the six text paragraphs of the chemistry science text (Cronbach's α = .79), such as: "Please write down everything you remember about Paragraph Two: Water surface tension." The retention test assessed students' memory of factual and conceptual information covered in the text.

All materials were presented in German.

3.3 Procedure

Within their school classes, students were randomly assigned to one of two groups, i.e., whether the first paragraph of the chemistry science text was paper-based (the Paper-Computer Sequence Group) or computer-based (the Computer-Paper Sequence Group). At the beginning of the study, students first completed the participant questionnaire and were then given the spatial ability pretest with a three-minute time limit. All students (i.e., both sequence groups) received pre-training on how to generate paper-based and computer-based drawings. The Computer-Paper Sequence Group was presented with the paper-based pre-training first and received the computer-based pre-training before starting the first paragraph on the computer. This order was chosen to avoid an additional unnecessary switch between paper- and computer-based parts of the lesson. For the same reason, the Paper-Computer Sequence Group began their pre-training on the computer and then did the paper part of the pre-training before starting with the first science paragraph on paper. In both computer- and paper-based parts of the pre-training students were asked to generate a drawing of a little man by means of given elements. After that, students were given the chemistry science text. Based on the respective condition, participants began reading the 6-paragraph chemistry text on paper or on the computer. Each paragraph was then alternately presented either on paper (with instructions to make a drawing on paper) or on a computer screen (with instructions to use drag-and-drop tools to make a drawing), as exemplified in Table 3.1.

In the main part of the lesson all students were instructed to read the science text for comprehension and to make drawings representing main ideas of the text, by hand for paragraphs presented on paper and using drag-and-drop for paragraphs presented on the computer screen.

To assess cognitive load, students were told to turn the page or to click on the ‘hint’ button when they were finished with generating the respective drawing on paper or on the computer-screen. Students were then guided to answer the respective question in the learning booklet concerning the perceived difficulty during working with the previous paragraph and to read the next paragraph on the computer or paper, depending on condition.

After students had pressed the ‘hint’ button on the screen, a ‘continue’ button appeared, but was blocked for approximately two minutes. This prevented students from skipping to the next computer-based paragraph before answering the appropriate perceived difficulty item, reading the next paragraph on paper, and then answering the next appropriate perceived difficulty item. On paper, students were told to turn the page when they were finished with generating the drawing, and then answered the respective difficulty item. On the next page the word ‘stop’ was printed in large, red letters, and the text on this page instructed the students to go back to the computer and to learn with the next paragraph on the computer. This procedure was repeated for every paragraph. After the last perceived difficulty item following Paragraph 6 (the last paragraph), both the learning booklet and the computer learning environment ended. Total study time for each student was recorded at the end of the learning task. Students then completed the Medium Preference Questionnaire.

Finally, students received the learning-outcome test to complete at their own pace without access to the learning materials. Overall, after instructions and the pre-training, students had approximately 70 minutes left to learn with the chemistry science text and to finish the posttest. They could decide on their own when they were finished with learning and subsequently also when they were finished with the posttest. Once students were finished with learning and completed the Medium Preference Questionnaire they got the posttest immediately, which means that the time between learning and the posttest was the same for every subject. All students were able to finish learning and the posttest within these 70 minutes.

After approximately five weeks, delayed learning effects were measured by giving the students the same posttest again as a follow-up test.[3]

This research was conducted in compliance with APA ethical principles.

3.4 Results

Scoring

The total number correct out of 80 determined the spatial ability score.

The chemistry posttest scores on each of the six open-ended questions for each learner were computed by counting the total number of correct solution ideas in written answers. There were four possible correct solution ideas for questions one, two, and three; three possible ideas for question four and five; and two possible ideas for question six. The correct solution ideas were extracted by the help of expert answers that were constructed by two student science teachers under supervision of the author. Two research assistants scored the students' answers with moderate inter-rater agreement over all six questions (Goodman-Kruskal gamma = .48). For the analyses concerning learning outcome, which will be described in the following section, we used tertile-split scores. We used these scores, because of the right skewed distribution of the learning outcome scores (basement effect, Figure 3.3) and the varying difficulty of the different items (see Figure 3.6).

[3] The same posttest was administered approximately five weeks later, but the data are not included in this thesis as they did not show significant differences or an interpretable tendency.

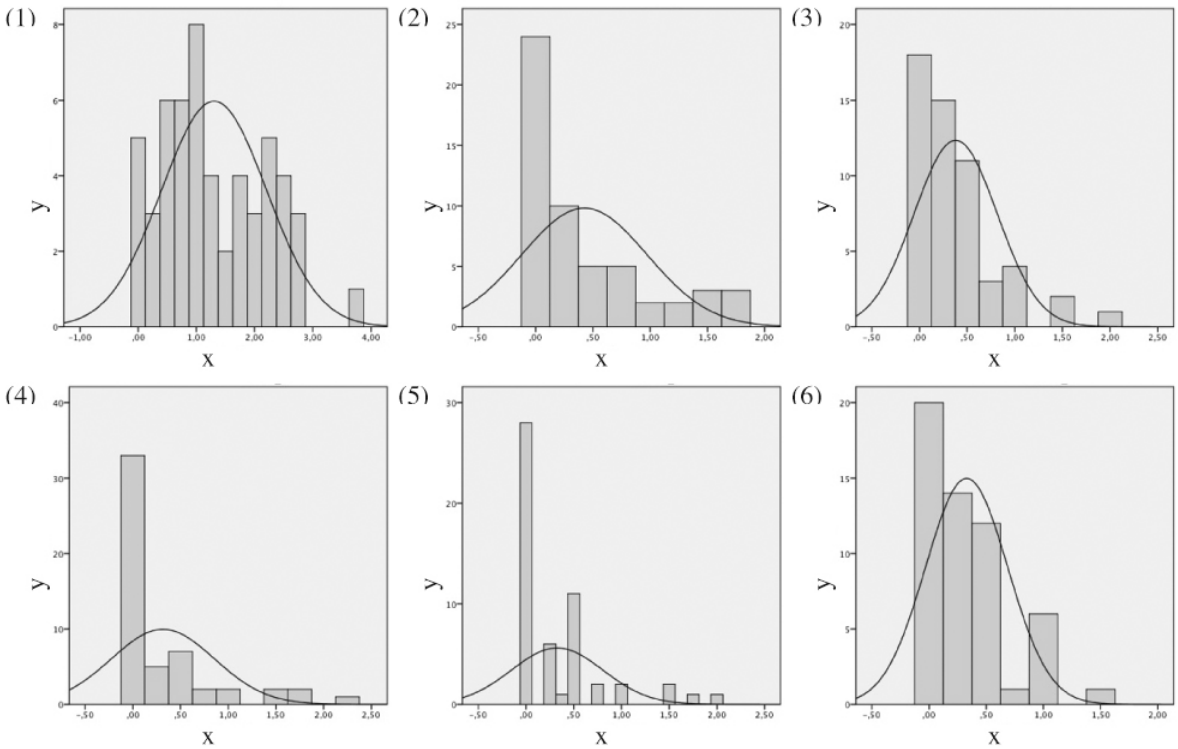

Figure 3.3 Frequencies of students' learning outcome scores (x-axes) for each of the six questions individually (1-6). Histograms of the questions two (2), three (3), four (4), five (5) and six (6) show a right skewed distribution.

The perceived difficulty scores of the six paragraphs, based on a 7-point Likert-Scale (see Material and Apparatus), were computed per item.

In order to assess the quality of learner-generated drawings we computed drawing accuracy scores for each of the six drawings, using an adapted coding scheme from Schmeck (2010), which we already used in Study I (Chapter 2). This yielded a maximum of eight point five points on drawing accuracy for Paragraph One, a maximum of seven points for Paragraph Two, eight points for Paragraph Three, two points for Paragraph Four, three points for Paragraph Five and finally a maximum of four points on drawing accuracy for the last Paragraph Six. The two research assistants scored each learner-generated drawing for each student, with mediocre inter-rater agreement between .24 and .72 (Goodman-Kruskal Gamma).

Finally, we computed the scores on the Medium Preference Questionnaire concerning students' enthusiasm to learn with paper or computer, their difficulties with the different mechanics of drawing, and their challenges in metacognition and learning per item. A score of 1 or 2 on the 4-point Likert-Scale indicated student's preference for the computer, whereas a score of 3 or 4 indicated student's preference for paper.

Are the Groups Equivalent on Basic Characteristics?

Before conducting any further analyses, we analyzed whether the two experimental groups differed on several basic characteristics. Chi-square analysis and analyses of variance, based on alpha = .05, indicated that there were no significant differences among the groups in the proportion of males and females, last chemistry grade, spatial ability score, or study time (all *p*s > .10). Additionally, we asked participants' chemistry teachers about the prior knowledge of their students concerning our chemistry science text. All teachers assured that their students had no prior knowledge about the content of the chemistry science text used in this study, mainly because in the students' curriculum this content is taught one school year later. Overall, we concluded that the groups were equivalent on basic characteristics.

Descriptives

In the next sections we will look at students' learning outcome, their perceived difficulty and the quality of their drawings when learning by means of the generative drawing strategy paper- and computer-based. The descriptives are given in Table 3.2, Table 3.3, and Figure 3.4.

Table 3.2
Means (Standard Deviations) of the Tertile-Split Learning Outcome Score (Upper Part), Students' Perceived Task Difficulty (Middle Part) and Drawing Accuracy (Bottom Part) on all six Text Paragraphs for Both Sequence Groups

	Paragraph	*Computer-Paper Group (N = 27)*		*Paper-Computer Group (N = 27)*	
		M	*SD*	*M*	*SD*
Learning Outcome	1	2.07	0.83	1.78	0.80
	2	1.96	0.94	1.89	0.89
	3	2.04	0.90	2.07	0.83
	4	2.07	0.83	1.41	0.80
	5	1.96	0.94	1.81	0.92
	6	2.04	0.90	1.70	0.82
		M	*SD*	*M*	*SD*
Perceived Difficulty	1	3.81	1.55	3.63	1.70
	2	3.67	1.04	3.55	1.34
	3	3.15	1.30	3.78	1.68
	4	3.70	1.20	3.04	1.53
	5	3.41	1.34	3.48	1.58
	6	3.44	1.70	2.61	1.57

			M	*SD*	*M*	*SD*
Drawing Accuracy	*54*	1	2.48	2.65	1.52	1.45
		2	1.37	1.52	0.94	1.10
		3	2.35	2.14	2.38	1.58
		4	0.44	0.61	0.52	0.62
		5	0.83	1.05	0.63	0.86
		6	0.88	1.11	1.05	1.09

Note. Grey Boxes = Text paragraphs were presented on the computer; White boxes = Text paragraphs were presented on paper.

Table 3.3
Means (Standard Deviations) and the Effect Size Cohen's d of the Tertile-Split Learning Outcome Score (Left Part), Students' Perceived Task Difficulty (Middle Part) and Drawing Accuracy (Right Part) for Text Paragraphs That Were Presented on a Computer and for Text Paragraphs That Were Presented on Paper (N = 54)

	Learning Outcome			*Perceived Difficulty*			*Drawing Accuracy*		
	M	*SD*	*d*	*M*	*SD*	*d*	*M*	*SD*	*d*
Computer	1.83	0.61	-0.24	3.30	1.13	-0.35	1.36	1.35	0.13
Paper	1.98	0.62		3.62	1.13		1.21	0.91	

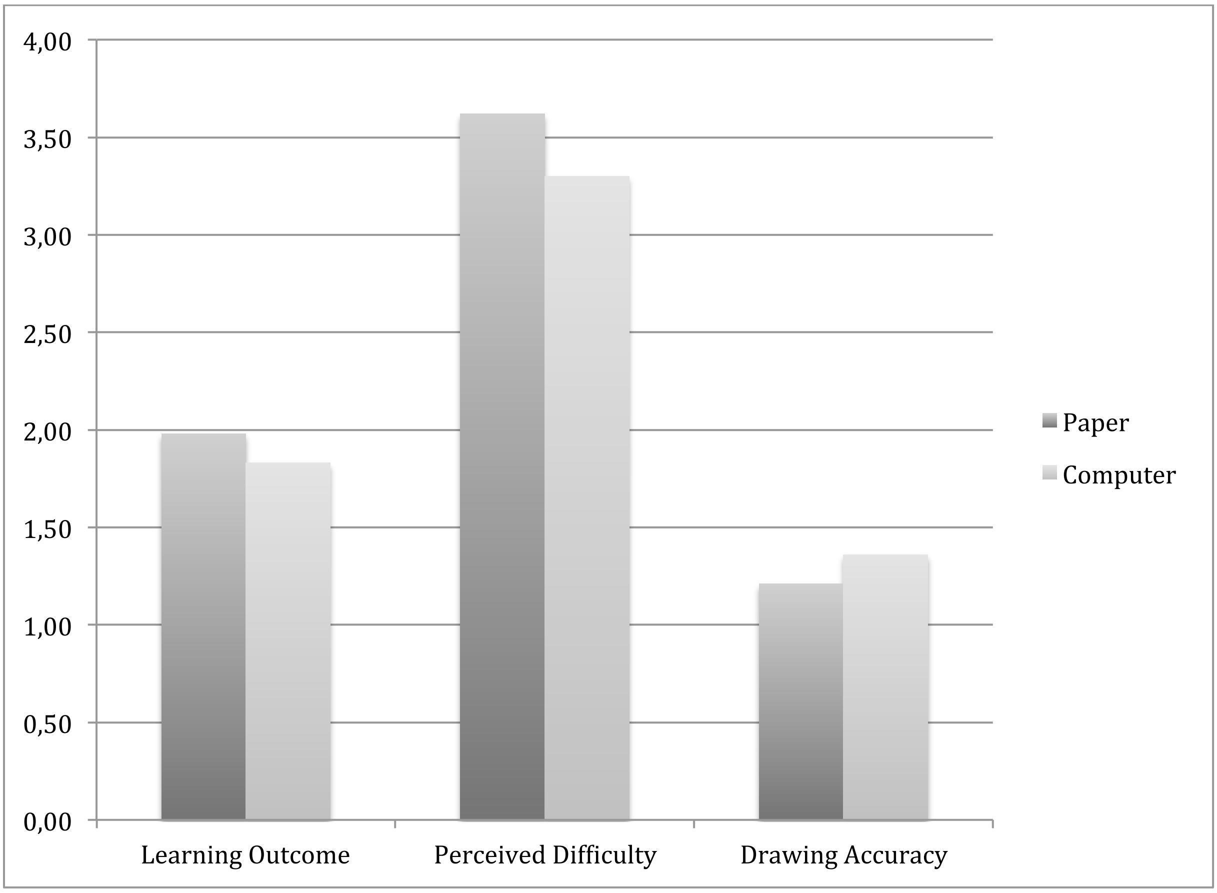

Figure 3.4 Students' learning outcome, perceived difficulty, and drawing accuracy of the paper-based material compared to students' learning outcome of the computer-based learning material.

Do Students Learn Better From Science Texts When Reading and Generating Drawings on Paper or on a Computer Screen?

One major goal of this study was to determine whether students learn better when learning from science texts on paper or on the computer. Therefore, in the present analysis, we focus on the learning outcome of content learned from paper-based and learned from computer-based learning material and whether there is a difference in performance between these two. For the analyses concerning learning outcome, which will be described in the following section we used tertile-split scores (see Table 3.2, Table 3.3, and Figure 3.4).

For every participant we computed two learning outcome scores, one for those text paragraphs that were presented on a computer and one for those text paragraphs that were presented on paper. A repeated-measures ANOVA with the presentation medium (computer-based and paper-based) as within-subjects factor, and with study time as covariate to test for a potential interaction with presentation medium, was computed. The covariate study time was included to make sure that a possible effect of the presentation medium was adjusted. The results show a significant main effect of the presentation medium on learning outcome $F(1, 52) = 4.60$, $p = .037$. Looking at the descriptive statistics in the left part of Table 3.3 and Figure 3.4, it is noticeable that students learn more when they read and generate drawings on paper than on a computer screen. Furthermore, there was a significant interaction of the type of presentation medium and study time $F(1, 52) = 11.31$, $p < .001$. This indicates that study time has different effects on students' learning outcome depending on which type of presentation medium students learned with. Correlations showed that learning outcome related to paper-based learning material was independent of study time (r = .001) whereas learning outcome related to computer-based learning material was significantly related to study time (r = .399) (see Figure 3.5).

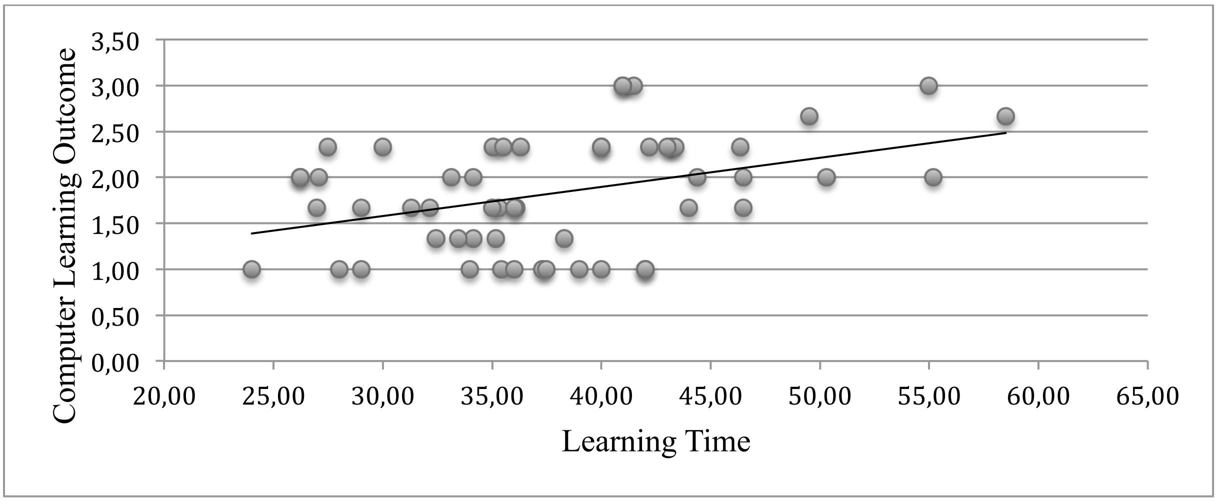

Figure 3.5 Scatterplot of computer-based learning outcome and learning time (in minutes).

Do Students Report Higher Perceived Difficulty When Reading and Generating Drawings on Paper or on a Computer Screen?

The previous section provided information about students' different learning performance when learning from a science text by means of the generative drawing strategy paper-based or computer-based. In the present analysis, we focus on whether students report more difficulties when they learn from science texts on paper or on the computer.

For every participant we computed two perceived difficulty scores, one for those text paragraphs that were presented on a computer and one for those text paragraphs that were presented on paper (see Table 3.3, middle part). A repeated-measures ANOVA with the presentation medium (computer-based and paper-based) as within-subjects factor and study time as covariate, to test for a potential interaction with presentation modus, was computed. The results show a significant main effect of the presentation medium on perceived difficulty $F(1, 52) = 6.60$, $p = .013$. The descriptive statistics (see Table 3.3, middle part, and Figure 3.4) reveal that students reported less perceived difficulty when working with the computer-based learning environment than with the paper-based learning environment. Figure 3.6 emphasizes that on all six chemistry science text paragraphs (with paragraph one as an exception) students perceived less difficulty when they worked computer-based instead of paper-based.

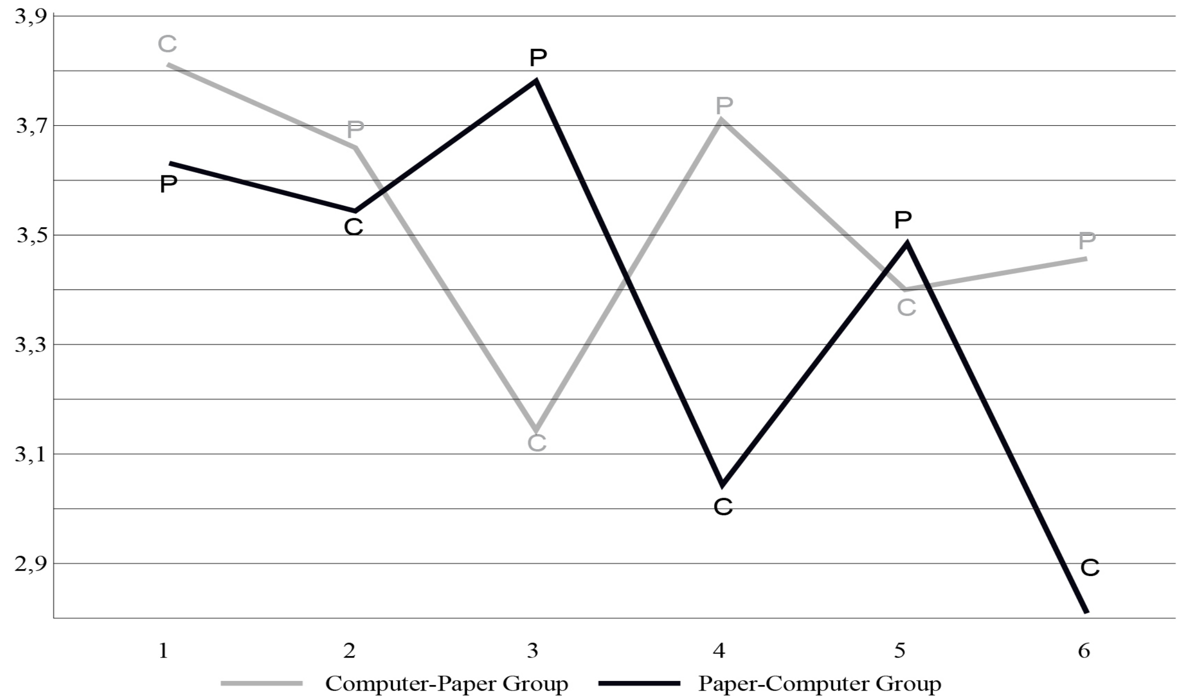

Figure 3.6 Distribution of students' perceived task difficulty on all six science text paragraphs. The two different colored lines present the two sequence groups i.e., one group began with the computer-based and the other group with the paper-based learning material. Each measurement point is labeled with a P or C, depending on whether students worked with the respective paragraph computer-based or paper-based.

Is the Quality of Drawings Related to Better Learning Outcomes?

In the present analysis, we focus on the quality of the drawings produced by the students in order to determine whether the quality of drawings is related to posttest performance. According to the prognostic drawing principle, initially found for hand-drawn student drawings (Schwamborn, Mayer, et al., 2010), and later also found with computer-based drawings (Study I, Chapter 2), we expect the quality of the computer-based drawings and paper-based drawings, produced during learning, both to be positively related to posttest learning outcome scores.

As a first step in testing whether the prognostic drawing principle is independent of the medium in which the learning text is presented and the drawings are generated, we computed for every participant two drawing accuracy scores, one for those text paragraphs that were presented on a computer and one for those text paragraphs that were presented on paper, based on the drawing accuracy raw scores (see Table 3.3). Using these pooled scores a repeated-measures ANOVA with the presentation medium (computer-based and paper-based) as within-subjects factor, shows no significant main effect of the presentation medium on the drawing accuracy respectively the quality of the drawings $F(1, 53) < 1$.

Second, correlation analyses revealed that the drawing accuracy score for computer-based drawings correlated significantly with learning outcome, both posttest scores related to computer-based paragraphs, $r = .52$, $p < .01$, and posttest scores related to paper-based paragraphs, $r = .41$, $p < .01$. For the drawing accuracy score for paper-based drawings, correlation analyses revealed that the accuracy score again correlated significantly with learning outcome, both posttest scores related to computer-based text paragraphs, $r = .41$, $p < .01$, and posttest scores related to paper-based text paragraphs, $r = .35$, $p < .01$. Additionally, there was a high correlation between the accuracy score for computer-based drawings and the accuracy score for paper-based drawings, $r = .50$, $p < .01$.

However, correlation analyses also revealed that the learning time correlated significantly with the drawing accuracy score for computer-based drawings, $r = .38$, $p < .01$, meaning that the longer learners worked with the computer-based material the higher is their drawing accuracy score for computer-based drawings (see Figure 3.7). There was no significant correlation between learning time and the drawing accuracy score for paper-based drawings.

This pattern of results shows a strong positive relation between the quality of students' drawings generated during learning and their performance on the posttests, regardless of whether the learning material was computer-based or paper-based. This is primary evidence in support of the prognostic drawing effect, which states that the quality of drawings during learning predicts the quality of posttest performance on measures of learning outcome.

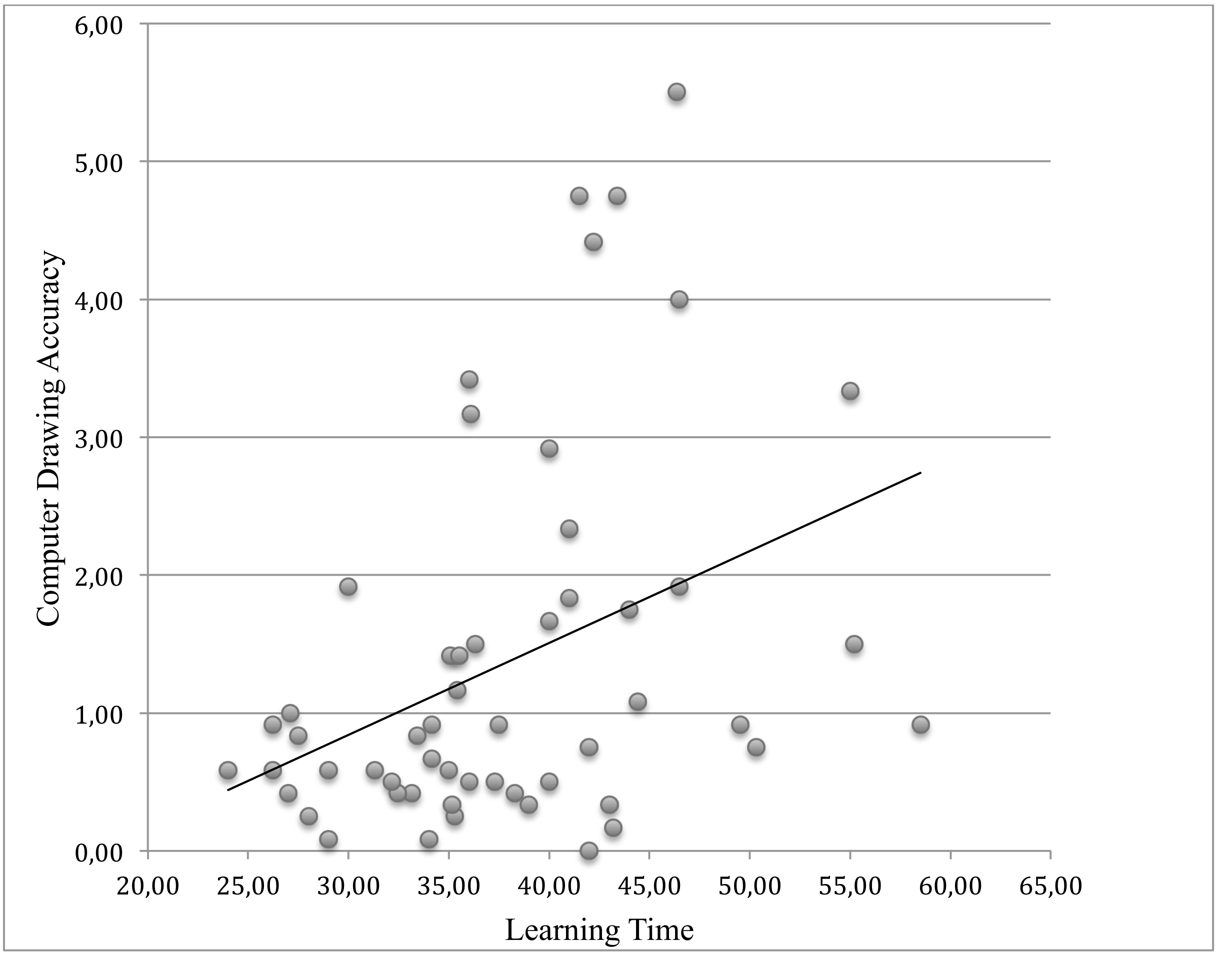

Figure 3.7 Scatterplot of the computer-based drawing accuracy score and learning time (in minutes).

Do Students Report Higher Enthusiasm, Difficulties with the Mechanics of Drawing, and Challenges in Learning When Reading and Generating Drawings on Paper or on the Computer?

Another major goal of this study was to determine which factors and underlying aspects of the computer-based learning environment compared to the paper-based learning environment may cause students' perceived difficulty. For the Medium Preference Questionnaire, we analyzed each item individually.

Table 3.4 summarizes the mean and standard deviation of each of the 13 items of the Medium Preference Questionnaire. One sample t-tests with a test value of 2.5 were executed for each item to evaluate whether the mean preference was significantly different from 2.5, the score on the 4-point scale at which no preference for computer nor for paper would be indicated. Because the taxonomie of the Medium Preference Questionnaire reflected all relevant steps and mechanics for generating drawings, we analysed each item individually to see differences concerning students' preference for learning medium in detail and be able to interpret them item-based. A Bonferroni correction was calculated by deviding the signicance level .05 of the t-test by 13, the number of the here individually tested hypothesis. After this correction these t-tests were significant for seven out of thirteen items.

The upper part of Table 3.4 shows the two items asking for the enthusiasm issue. Looking at the enjoyment students had while generating drawings (Item 1) the mean is 1.76 (SD = 0.67) which is significantly different from 2.5, $t(53) = -8.11$, $p < .001$. This indicates a preference to work with the computer-based material in place of the paper-based material. The effect size of $d = 1.10$ (d = t/square root (n)) indicates a large effect. Concerning Item 13 about students' preferred medium to work with in the future, the mean is 1.87 (SD = 0.58), which is significantly different from 2.5, $t(53) = -7.91$, $p < .001$, indicating a preference for the computer-based material. The effect size of $d = 1.09$ indicates a large effect.

The middle part of Table 3.4 presents the items asking for the difficulties-with-the-drawing-mechanics issue. Looking at the item about with which learning environment it was easier for students to generate drawings (Item 2), the mean is 2.06 (SD = 0.76), which is significantly different from 2.5, $t(53) = -4.28$, $p < .001$, indicating a preference for the computer-based learning environment. The effect size of $d = 0.58$ indicates a medium effect. In addition, for Item 5 about where it was easier to choose relevant elements from the toolbar, the mean is 2.09 (SD = 0.79), which is significantly different from 2.5, $t(52) = -3.73$, $p < .001$, indicating a preference for the computer-based learning environment. The effect size of $d = 0.52$ indicates a medium effect. However, concerning Item 7 about the orientation of the given drawing elements, the mean is 2.89 (SD = 0.90), which is significantly different from 2.5, $t(53) = 3.16$, $p = .003$, indicating a preference for the paper-based material. The effect size of $d = 0.43$ indicates a small effect.

Finally, the bottom part of Table 3.4 shows the results for the metacognition-and-learning-challenges issue. Regarding Item 8 that asked where it was easier for students to correct their drawings, the mean is 1.59 (SD = 0.79), which is significantly different from 2.5, $t(53) = -8.45$, $p < .001$, indicating a preference for the computer-based learning environment. The effect size of $d = 1.15$ indicates a large effect. Additionally, for Item 12 that asked where students actually improved more of their drawings, the mean is 2.05 (SD = 0.81) which is significantly different from 2.5, $t(53) = -4.03$, $p < .001$, indicating a preference for the computer-based learning environment. The effect size of $d = 0.55$ indicates a medium effect.

Table 3.4
Means (Standard Deviations) of the 13 Items of the Medium Preference Questionnaire

Item No.	*N*	*M*	*SD*
(Enthusiasm)			
01. Drawing the pictures was...	54	1.76***	0.67
1) o strikingly more fun on the computer,			
2) o a little more fun on the computer,			
3) o a little more fun on paper,			
4) o strikingly more fun on paper			
13. In the future I would....	54	1.87***	0.58
1) o clearly prefer working with the computer,			
2) o prefer working on the computer,			
3) o prefer working on paper,			
4) o clearly prefer working on paper			
(Difficulty with Mechanics)			
02. To draw the pictures was...	54	2.06***	0.76
1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
03. To begin with drawing was...	54	2.45	0.66
1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
04. To draw the pictures as I wanted them to draw was...	54	2.31	0.94
1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
05. To chose the elements to draw the pictures, for example the hydrogen molecule, surfactants etc. was...	53	2.09***	0.79
1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
06. To place the drawing-elements to the correct position on/in the predrawn drawing background was...	53	2.35	0.92

1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
07. To orient the drawing-elements for me it was...	54	2.89**	0.90
1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
(Metacognition and Learning)			
08. To correct/improve the pictures during respectively after drawing for me it was...	54	1.59***	0.79
1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
09. To understand the content of the text paragraphs, for me it was...	53	2.70	0.72
1) o strikingly more easy on the computer,			
2) o a little more easy on the computer,			
3) o a little more easy on paper,			
4) o strikingly more easy on paper			
10. I thought about the picture I should draw – before I started to draw...	54	2.65	0.65
1) o strikingly more often on the computer,			
2) o a little more often on the computer,			
3) o a little more often on paper,			
4) o strikingly often fun on paper			
11. To go back in the text, to reread information during drawing, I did...	54	2.50	0.84
1) o strikingly more often on the computer,			
2) o a little more often on the computer,			
3) o a little more often on paper,			
4) o strikingly often fun on paper			
12. During the drawing process I corrected/improved my drawings...	54	2.05***	0.81
1) o strikingly more often on the computer,			
2) o a little more often on the computer,			
3) o a little more often on paper,			
4) o strikingly often fun on paper			

*Note.*Significance levels: * $p < .038$ (after bonferroni correction), ** $p < .01$, and *** $p < .001$ based (two tailed); means < 2.5 students decide in favor for the computer, means > 2.5 students decide in favor for paper.

3.5 Discussion and Scientific Significance

Empirical Contributions

From an empirical point of view, our results show that there is a difference in students’ learning outcome depending on whether students read and generate drawings on paper or on a computer screen. Results show that students learn more when they learn from a science text using the generative drawing strategy on paper (and drawing by hand) than on a computer screen (and drawing via drag-and-drop). Thus, there are differences in the effectiveness of computer-based and paper-based learning materials. Although appropriate instructions are given to students during learning within the paper-based and computer-based text paragraphs (Study I, Chapter 2; Schwamborn et al., 2011; Schwamborn, Mayer et al., 2010), it matters whether generative drawing construction is used paper-based or computer-based. Additionally, results show a correlation of learning outcome related to computer-based learning material and study time, meaning that the longer students work with the computer-based material the higher is their learning outcome recpectively they learn more.

Our results also show that students report to perceive significantly less difficulty when learning with the computer-based text paragraphs than with the paper-based text paragraphs of the learning material. Thus, results show that the presentation medium has an effect on perceived difficulty.

Another empirical contribution of this study is that the quality of the generated drawings is independent of the medium in which the learning text is presented and the drawings are generated. However, results show that the accuracy respectively the quality of drawings, generated via a computer tool, are positively correlated to students’ posttest performance according to computer-based as well as paper-based learned science content. In line with previous research, we found that the same is true for the accuracy of hand-drawn drawings. This accuracy was related to students’ posttest performance according to paper-based as well as computer-based learned science content. This is evidence in support of the prognostic drawing effect, which states that the quality of drawings during learning predicts the quality of posttest performance on measures of learning outcome.

Additionally, correlation analyses also revealed that the learning time correlated significantly with the drawing accuracy score for computer-based drawings. This means that the longer learners worked with the computer-based material the better is the quality of their computer-based drawings.

An additional empirical contribution of this study is that students report to experience and to have different kinds of difficulties, challenges and preferences when using computer-based or paper-based approaches to generate drawings during learning from a chemistry text. Overall, students stated that they experienced fewer difficulties when learning with the computer, and accordingly most of them indicated they would rather work with the computer in the future.

Theoretical Contributions

From a theoretical point of view, our results are consistent with assumptions derived from the generative drawing principle (Leutner & Schmeck, 2014; Schwamborn, Mayer et al., 2010) and the first study of this thesis (Study I, Chapter 2). Looking at students' learning outcome, the results are consistent with paper-based studies concerning generative drawing (Leopold & Leutner, 2012; Schmeck, 2010; Schwamborn, Mayer, Thillmann, Leopold, & Leutner, 2012; Schwamborn, Thillmann, Leopold, Sumfleth, & Leutner, 2010) and partly with our Study I (Chapter 2). Results show that learning outcomes for content students learned from paper-based material were significantly higher than learning outcomes for content learned from computer-based material. This partly supports findings from Study I (Chapter 2) and findings from Schwamborn, Mayer et al. (2010), Schmeck et al. (2010) as well as from Leutner and Schmeck (2014): Although the generative drawing principle was extendable to computer-based learning Study I (Chapter 2), in comparison the effect sizes of paper-based generative drawing on learning outcome were higher than the effect sizes of computer-based generative drawing on learning outcome (for an overview see Leutner & Schmeck, 2014).

At first sight controversially, we found that students rated their perceived difficulty higher (as measured by the perceived difficulty item of Kalyuga et al., 1999) when they learned with the paper-based material than with the computer-based material, which seems to contradict the assumption that computer-based learning environments are still a bit too intrusive when using the learner-generated drawing strategy (Study I, Chapter 2). However, the combination of the two results (i.e., learning outcomes for content students learned from paper-based material were significantly higher than learning outcomes for content learned from computer-based material and that students rated their perceived difficulty higher when they learned with the paper-based than with the computer-based material) contradicts the Cognitive Theory of Multimedia Learning (CTML; Mayer, 2009) and the Cognitive Load Theory (CLT; Chandler & Sweller, 1991; Sweller, Ayres, & Kalyuga, 2011). According to these theories, perceived difficulty is believed to reflect extraneous cognitive load. Although measures that were used here cannot measure cognitive overload, comparing cognitive load for the two different media, according to the CTML (Mayer, 2009) and CLT (Chandler &

Sweller, 1991; Sweller, Ayres, & Kalyuga, 2011) we expected that, when students perceive less difficulty working with the computer-based learning material they should have enough space within their working memory for generative processing. Thus, computer-based learning material was expected to be the best suited media for learning. Additionally, when students rate their perceived difficulty higher in paper-based learning environments, it was expected that students score lower on learning outcome of content learned in this environment. However, this was not what we found in this study. For the CTML (Mayer, 2009) and CLT (Chandler & Sweller, 1991; Sweller, Ayres, & Kalyuga, 2011) this means that their assumption that more perceived difficulty leads to less learning outcome must be questioned when comparing generative drawing in computer-based and paper-based learning environments.

Additionally, our results again replicated the prognostic drawing principle in paper-based as well as in computer-based learning environments and therefore results are again in line with the Theory of Generative Drawing (van Meter, 2001, 2005; van Meter & Firetto, 2013), which states that students who engage effectively in generating visualizations tend to build up a more coherent idea of the learning content and therefore construct meaningful learning outcomes. The accuracy of the drawings reflects the quality of the generative process during learning and consequently is related to learning outcome scores. However, it does not seem to matter whether students learn with paper-based or with computer-based material and how students generate the drawings, by hand or via drag-and-drop.

Finally, underlying aspects of students' perceived difficulty of drawing were investigated. Thus, our study additionally fills a gap in the Cognitive Load Theory (Chandler & Sweller, 1991; Sweller, Ayres, & Kalyuga, 2011) about specific difficulties students can perceive within learning environments using generative drawing. With our Medium Preference Questionnaire we tried to provide a deeper insight into perceived difficulty, i.e. we found it important to develop a questionnaire that differentiates possible difficulties students might try to express when they are asked how difficult a learning unit was for them. Additionally, the results concerning the underlying aspects of perceived difficulty provide information that can partly explain our contradictory results: less perceived difficulty when working with the computer-based learning material but lower learning outcome scores, at the same time.

Looking at the specific difficulties students encountered, derived from the results of our Medium Preference Questionnaire, it seems that students perceived challenges that can lead to different manifestations of cognitive load (cf. DeLeeuw & Mayer, 2008). Concerning results about enthusiasm from the Medium Preference Questionnaire, students significantly prefer to work with the computer in the future (Item 13) and have more fun when generating the drawings computer-based (Item 1). Because, students have more fun and prefer to work with the computer in the future, it must be assumed that students are more motivated (motivation is an "activating alignment of the current conduct of life to a positively evaluated target state", Rheinberg, 2004, p. 17) when learning computer-based instead of paper-based. Additionally because, there is a positive correlation between motivation and learning (Rheinberg & Fries, 1998), a consequence can be an increased demand of computer-based learning from students as well as from teachers.

Looking at the difficulties students had with the mechanics of drawing (based on the Medium Preference Questionnaire), students reported that it was significantly easier for them to generate drawings in general (Item 2) on the computer than on paper. Additionally, students reported that it was significantly easier for them on the computer to choose the drawing elements to draw the pictures (Item 5). However, for using the generative drawing strategy in practice it is important to note that, according to student data, orienting the given drawing elements was easier with paper-based material than on the computer (Item 7).

Concerning metacognition and learning challenges, students indicated a significant preference for learning with computer-based materials for two of the five items. Students stated that it was significantly easier for them to correct their drawings (Item 8) and actually improve more of their drawings (Item 12) when they learned with the computer-based material. On the one hand, these results show that students seem to perceive less difficulty in the computer-based learning environment, leaving more cognitive resources available for germane cognitive load/generative processing, fostering meaningful learning. On the other hand, whether correcting (and improving) is easier in the computer-based environment, there is a risk of students not engaging in enough cognitive as well as metacognitve activities. To put it simply, because it is easy for students to change and correct their drawings, it is possible that they do not bother to think enough before drawing, which might lead to not building a sufficient mental model and, as a consequence, lower learning outcome. Results of the ANOVA concerning learning outcome support this, by showing that students learned less when learning with the computer-based material. Clearly, a higher learning outcome depends on how well a learner understands the information, thus here it seems that students understand more of the science content when learning with the paper-based materials.

Looking once more at the results of the items asking about metacognition and learning, students indicated twice (Item 8 and Item 12) that they significantly prefer the computer-based material over and above the paper-based material. However, these two items could, on the one hand, be categorized as difficulty with the mechanics of the drawing (thus a form of extraneous cognitive load) and, on the other hand, as learning-based load (a form of germane cognitive load; Sweller et al, 1998). Thus, the two itmes also indirectly retrieve germane load, which is needed for successful learning outcomes.

Nevertheless, with the strategy of generative drawing, our aim is to foster processes like metacognition (and, as a result, generative processing respectively germane cognitive load) to achieve deep understanding (Mayer, 2009) as well as learning. Additionally, generative theories of learning posit that people learn better when they engage in generative processing during learning, that is, cognitive activities aimed at making sense of the material (Mayer, 2009). In this study, results concerning students' learning outcome indicated that there seems to be more generative processing, respectively germane cognitive load within paper-based learning environments (students using paper-based material).

However, some of the results could explain the mismatch between the higher perceived difficulty and the higher score on learning outcome for the paper-based learning environment. Students have a significantly higher motivation when learning on the computer and it is easier for them to generate and correct respectively improve the drawings there, and thus they are supposed to have less extraneous load in the computer-based learning environment.

In summary, when comparing generative drawing within paper-based and computer-based learning directly, using the learning strategy within the paper-based environment results in higher learning outcome. Thus, regarding the Theory of Generative Drawing (van Meter, 2001, 2005; van Meter & Firetto, 2013) it seems that the generative drawing principle (Leutner & Schmeck, 2014; Schwamborn, Mayer et al., 2010) is more effective using paper-based drawing. However, students perceived learning in the computer-based environement as less difficult, which according to the Cognitive Load Theory (Chandler & Sweller, 1991; Sweller, Ayres, & Kalyuga, 2011) means that there should be more cognitive resources available for generative processing, thus meaningful learning respectively a higher learning outcome. Because we found exactly the opposite here, the CLT must be reconsidered when comparing computer-based and paper-based drawing. However, the results concerning our Medium Preference Questionnaire provide information that can partly explain the contradictory results. One possible explanation for the contradictory result could be that students, due to the perceived simplicity of the computer-based environment do not engage in enough cognitive and metacognitive processing. Additionally, the results give pointers to possible shortcomings of the usage of only one item by Kalyuga et al. (1999), to ask for extraneaous coginitve load.

Practical Contributions

All results concerning the underlying aspects of perceived difficulty and medium preference give important indications on how to organize and design learning environments for optimizing the learning strategy of generative drawing.

An important derived practical contribution is that the drag-and-drop mechanics seem to be easier to handle than drawing by hand. In other words, it was easier for students to generate the drawings in general and to choose the elements to draw the picture, as well as to correct and improve their drawings when using drag-and-drop. However, whether these processes are easier, besides the positive effect of decreasing extraneous processing, there is a risk that learners do not engage in enough cognitive and metacognitive processes: They might draw carelessly without contemplating and planning before beginning to draw. The resulting learning might be relatively shallow. Another practical contribution is that orienting the given drawing elements seems to be more difficult with drag-and-drop than with paper-based material, which was likely a problem of this specific computer-based environment.

Thus, in addition with our significant finding that students have higher learning outcome scores respectively learn more when they learn from a science text using the generative drawing strategy on paper we propose the use of paper-based text combined with on-screen generative drawing with mechanics that mimic drawing by hand and at the same time give the opportunity to eliminate parts of the drawing quickly and easily. This would be possible, for example, with a tablet computer. Using a tablet computer, can on the one hand meet demands of students and teachers concerning more computer-based learning in real school life wich are likely to arise for example because of students' higher motivation to work with computer-based material. On the other hand, drawing using a tablet computer is similar to drawing using a pencil, which in general is a familiar and therefore a more embodied learning procedure for students, whereas drawing using drag-and-drop by means of a track pad or mouse of course is not the same as drawing by hand and using a pencil. Overall, it would be recommendable to combine benefits of both environments, so that disadvantages of each are minimized, causing less extraneous processing and leaving more cognitive resources available for generative processing, fostering meaningful learning (Mayer, 2009; Sweller, 1999, 2005).

Limitations and Future Directions

The present study was limited in some areas that should be investigated in future studies.

Although we did find a significant effect of the learning medium on the learning outcome, it is the first study in which the comparison between generative drawing with paper-based and computer-based approaches is addressed directly. Thus, more studies must be conducted with this design to replicate the results, especially those concerning the inconsistent results of learning outcome and cognitive load here in the form of perceived difficulty.

Another possible explanation for the inconsistent findings concerning the learning outcome and perceived difficulty must be investigated in future studies, namely *generative processing underutilization* (Mayer, 2009). According to Mayer (2009), generative processing underutilization could occur when learning material is presented in an unattractive way, for example when it is boring and therefore the learner does not put much effort into trying to understand the material. However, it is conceivable that generative processing underutilization can also take place when the learning material is not demanding enough. Perhaps this happened in the computer-based learning environment when it was easier for the students to generate drawings and also to improve and delete all or parts of the drawing. This could be a situation in which students have cognitive capacity available but perhaps they do not choose to use it for making sense of the material (Mayer, 2009).

Additionally, we measured cognitive load by means of only one item, namely the perceived difficulty item of Kalyuga et al. (1999). Future studies should measure extraneous cognitive load by means of the item of Kalyuga et al. (1999) and additionally the item of Paas (1992), which asks about invested mental effort. Furthermore, in future studies the cognitive load items should also be presented paper-based as well as computer-based. Students should answer the items in a paper-based booklet or on the computer screen depending on the medium they worked with in the previous paragraph. However, both the item we used and the item of Paas (1992) are subjective measurements, which could be criticized.

In consideration of the results concerning the Medium Preference Questionnaire, it is important to examine the reliability of the questionnaire in more studies, under consistent conditions. Additioanlly, regarding Item 9 and 10, which only showed a tendency (not significant and therefore not discussed in the results section) of students preferring the paper-based learning environment, it would be interesting to have more results, because these items are supposed to be able to explain the higher learning outcome in the paper-based environment.

Moreover, our study did not include a control group that only read the chemistry science text and did not generate drawings. Having a control group would give the chance to replicate the effect of generating drawings on the learning outcome in comparison to learning by just reading the science text. Additionally, our study was conducted with only one science content, and results can therefore not be generalized to other science contents.

Overall, future research is needed to determine whether the effects of the generative drawing principle can be strengthened by a combined computer-based and paper-based learning environment, using drawing mechanics that are more natural for students. The hope would be that this would minimize extraneous processing but also force germane load, thus generative processing, by being not too easy in terms of improving and deleting the drawings. In particular, it would be useful to incorporate a tablet computer in the learning environment, which would allow students to use a pen but still work with a computer as the medium. Additionally, the science content should be presented as a paper-based text, to which students are used to, due to the usual use of school books and worksheets.

3.6 References

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4 Joint Discussion

In view of the fact that students have problems with the cognitively highly demanding processes of text comprehension when reading complex and difficult expository texts (Naumann, Artelt, Schneider, & Stanat, 2010), particularly when learning scientific concepts (Driver, Leach, Scott, & Wood-Robinson, 1994), the present dissertation aims to further investigate the effect of the generative drawing strategy on learning outcome from science text, thereby focusing on computer-based generative drawing. Prior research indicates that an effective alternative to purely learning from text is to use multimedia presentation, in which students learn from both text and pictures (Mayer, 2009; Schnotz, 2005; Schnotz & Bannert, 1999). Learning with multimedia presentations has been proven to be effective in paper-based learning environments (e.g., Mayer, 1989; Mayer & Anderson, 1991, 1992; Mayer & Gallini, 1990; Moreno & Mayer, 1999; Plass, Chun, Mayer, & Leutner, 1998; Schwamborn, Thillmann, Leopold, Sumfleth, & Leutner, 2010) as well as in computer-based learning environments (e.g., Brünken, Steinbacher, Schnotz, & Leutner 2001; Mayer & Moreno, 2002; Schmidt-Weigand, 2006; Schwamborn, Thillmann, Opfermann, & Leutner, 2011). Another approach to foster students' text comprehension is the generative drawing strategy (van Meter & Firetto, 2013; van Meter & Garner, 2005), which asks students to generate drawings as they read text. Studies concerning generative drawing on paper showed that it enhances students' learning from text (Leopold & Leutner, 2012; Schmeck, Mayer, Opfermann, Pfeiffer, & Leutner, 2014; Schwamborn, Mayer, Thillmann, Leopold, & Leutner, 2010; Schwamborn, Thillmann et al., 2010; van Meter & Garner, 2005). However, research results on the effectiveness of computer-based generative drawing are very rare with one study, which did not show positive effects on text comprehension (Schwamborn et al., 2011). To further investigate whether using computer-based generative drawing has a positive effect on learning outcome concerning science text (for the purpose of a replication and an extension of the existing state of research) and to investigate which medium is better to learn with, we conducted two studies. These studies systematically analyzed whether the generative drawing principle could be extended to computer-based learning (applying an adapted version of the learning material taken from Schwamborn et al., 2011; and Schwamborn, Opfermann, Pfeiffer, Sandmann, & Leutner, 2012). Put simply, we investigated if drawing while reading a scientific text on a computer screen enhances students' learning outcome. Finally we examined which medium is better to learn with when they are compared directly.

In Study I of this thesis (Chapter 2) we tested whether the generative drawing principle (i.e., creating drawings while reading a scientific text causes generative processing that leads to better learning outcomes) and the prognostic drawing principle (i.e., the accuracy of the generated pictures correlates positively with the learning outcome) can be applied to computer-based learning. Students read two onscreen science texts and were either instructed to learn with the text and an instructor-provided picture, or were instructed to learn with the text and generate drawings concerning the text content on their own, or both, or neither (the control group), followed by posttests of transfer, retention, and drawing as measures of learning outcomes. The results for both lessons combined were consistent with the generative drawing principle (Schwamborn, Mayer et al., 2010): Students who were instructed to generate drawings during learning within a computer-based learning environment scored higher on learning outcome tests. In addition, results provide strong and consistent support for the prognostic drawing principle (Schwamborn, Mayer et al., 2010). Results of Study I show, for the first time, that the generative drawing principle can be extended to computer-based learning environments. Additionally, the results provide strong and consistent support for the prognostic drawing principle. Thus, the results suggest that the generative drawing principle as well as the prognostic drawing principle can be extended to computer-based learning environments, when extraneous processing caused by the specific mechanics of generating computer-based drawings is reduced. However, group differences were found concerning the perceived difficulty (for the first time measured online), suggesting that generating drawings was perceived as adding difficulty to learning tasks. Adding difficulty ratings as a covariate strengthened the finding of a positive effect of computer-based drawing on learning, by showing additional positive effects of generative drawing on retention posttests and larger effect size of the positive effects on learning outcome already found in the previous analysis.

In Study II of this thesis (Chapter 3) we examined the contrast between drawing by hand versus drawing by computer to further investigate the effect of generative drawing in different learning environments and in different media. Students in Study II were instructed to read a 6-paragraph science text, in which paragraphs were alternately presented on paper (with instructions to create a drawing by hand) and on a computer screen (with instructions to use a drag-and-drop interface to create a drawing). Additionally, we measured perceived difficulty after every paragraph, thus online. Results show that students learn more when they learn from a science text using the generative drawing strategy on paper (and drawing by hand) than on a computer screen (and drawing via drag-and-drop). Thus, there are differences in the effectiveness of computer-based and paper-based learning material. Results also revealed that students reported more perceived difficulty when working with a paragraph in the paper-based learning environment than in the computer-based learning environment. Thus, results show that the presentation medium has an effect on perceived difficulty. On a subsequent questionnaire, students generally reported fewer difficulties when generating drawings by drag-and-drop on the computer. Students reported that they would rather work with the computer in the future, and have more fun when generating the drawings computer-based. Additionally, students reported that it was significantly easier for them to generate drawings in general and to choose the drawing elements to draw the pictures on the computer than on paper. However, orienting the given drawing elements was in contrast easier with paper-based material than on the computer. Looking at metacognition and learning challenges, students stated that it was significantly easier for them to correct their drawings and actually improve more of their drawings when they learned with the computer-based material. On the one hand, these results show that students seem to perceive less extraneous load in the computer-based learning environment, which should leave more cognitive resources available for germane cognitive load respectively generative processing, fostering meaningful learning. On the other hand, that correcting (and improving) is easier in the computer-based environment, creates a risk of students not engaging in enough cognitive as well as metacognitve activities, which could explain the mismatch between the higher perceived difficulty and the higher score on learning outcome for the paper-based learning environment. Finally, the prognostic drawing principle was supported in paper-based as well as in computer-based learning environments.

4.1 Major Results

We proposed several research questions. Based on our results, we can answer these questions as follows:

1) **Do people learn better from a science text when they are asked to generate computer-based drawings representing the main ideas of the text? Thus, is the generative drawing principle (i.e., creating drawings while reading a scientific text causes generative processing that leads to better learning outcomes) extendable to computer-based learning?**

   The results of Study I (Chapter 2) revealed that students who were instructed to generate computer-based drawings while reading a chemistry text on the computer screen scored higher on posttests of transfer and drawing, but not on retention, as compared to students who did not draw during learning. When students read a computer-based biology text instead and were instructed to generate computer-based drawings they scored higher on posttest scores on drawing but not on transfer or retention. Overall, there is some evidence for the generative drawing principle in computer-based learning environments, because results of Study I also revealed that students who generated computer-based drawings while reading a science text scored higher on posttest scores on transfer and drawing but not on retention, for the chemistry and biology science texts combined.

2) **Can the prognostic drawing principle (i.e., the accuracy of the generated drawings correlates positively with the learning outcome) (a) be generalized to computer-based learning, and (b) is the prognostic drawing principle independent of the medium (paper vs. computer) students learn with?**

Study I and Study II provided valuable results to answer these questions:

(a) Study I showed that students' scores on drawing accuracy (the proportion correct in computer-based drawings) produced during chemistry learning correlated significantly with each of the three posttest measures for the chemistry science text. The same applies to accuracy scores of computer-based drawings that students produced during learning with the biology science text and the corresponding three posttest measures for the biology science text. Additionally, findings of Study I showed that students who were classified as high-accuracy drawers (by means of a median split) concerning both the chemistry drawings and biology drawings significantly outperformed low-accuracy drawers on each of the posttest scores for the respectively content. The primary evidence in support of the prognostic drawing effect within computer-based learning is the positive relation between the quality of students' computer-based generated drawings during learning and their performance on the posttests. In summary it can be said that these results indicate that the prognostic drawing principle can be generalized to computer-based learning, because students who are able to use the learning strategy of computer-based generative drawing successfully (i.e., producing high quality drawings) gain better text comprehension and therefore benefit more from this learning strategy.

(b) Study II further tested whether the quality of computer-based and paper-based drawings is related to posttest performance, as suggested by Study I and results from Schwamborn, Mayer, and their colleagues (2010), and whether the prognostic drawing principle is independent of the medium. Results indicate that the drawing accuracy score for computer-based drawings (produced during computer-based learning) as well as for paper-based drawings (produced during paper-based learning) both correlate significantly with posttest scores related to computer-based paragraphs as well as to paper-based paragraphs. Thus, the quality of computer-based drawings and paper-based drawings produced during learning (on the computer or on paper, respectively) are both positively related to posttest scores. Overall, results indicate that students who are able to use the learning strategy of generative drawing successfully (i.e., producing high quality drawings) gain better text comprehension and therefore benefit more from this learning strategy, which is true for both computer-based and paper-based drawing. Thus, the prognostic drawing principle is independent of the medium students learn with.

3) **Do students report higher cognitive load when they are instructed to generate drawings while reading a science text using a computer-based interface (a) and is there an influence of cognitive load on the effect of generative drawing (b)?**
    (a) Cognitive load in Study I was measured online (i.e., immediately after learning with each science text paragraph) by means of two items asking students about their mental effort and about their perceived difficulty during learning. Results of this study show that students' perceived difficulty during learning was significantly higher within both science lessons for the generation groups than for the groups that did not generate drawings. Overall, these results suggest that generating drawings was perceived as adding difficulty to the learning task and this may be an indication of increased cognitive load during learning.
    (b) Additionally, in Study I it becomes apparent that adding the perceived difficulty rating as a covariate preserved and strengthened the conclusion that computer-based drawing has positive effects on learning outcomes. Besides the same pattern of significant effects with perceived difficulty as a covariate, additional effects of generating drawings on retention were found. Thus, adding the difficulty rating into the statistical model served to preserve and strengthen the previous conclusion (showing larger effect sizes) that computer-based drawing has positive effects on learning outcomes.
4) **Is the multimedia effect (i.e., that students learn better when they receive instructor-provided illustrations while reading a science text) replicable (a) and is there a specific effect of the combination of both learning with instructor-provided illustrations and generative drawing (b)?**

(a) As Study I was partly a replication of a study by Schwamborn et al. (2011) we also looked at whether there was evidence for the multimedia effect. The results show small and inconsistent effect sizes on retention and transfer posttests. Concerning the chemistry text we even found a negative main effect of presenting illustrations on the drawing scores, but when the two science lessons were combined, there was a positive main effect of giving illustrations while reading on the drawing scores.

(b) Additionally, because there were no significant interaction effects of generative drawing and provided illustrations in Study I, the generation of drawings is not moderated by the presentation of illustrations as well as vice versa. Thus, the multimedia effect is not moderated by the generation of drawings.

5) **Do students need more study time when they are asked to generate drawings while reading a science text on the computer?**

In Study I the study time was self-paced by the students and was measured by means of timestamps. It was therefore important for us to focus on differences in study time between the groups who generated drawings and those who did not. Results revealed that students' study time was significantly higher for the generation groups than for the groups that did not generate drawings, which is true for both science lessons. Asking students to generate drawings added substantially to study time, because of cognitive and metacognitive, as well as mechanical processing during suitable drawing. However, looking at the learning outcome of the groups who generated drawings as well as on their study time, it seems that a sufficient study time can counteract the higher cognitive load caused by the drawing mechanics. Thus, students' averaged study time showed self-generated drawing as to be a relative efficient learning strategy, meaning that althoug it costs more study time it pays off regarding the learning outcome.

The following questions are foremost answered by Study II, which was the first study to directly compare the effects of paper-based and computer-based generative drawing.

6) **Do students learn better from science texts when they generate paper-based or computer-based drawings?**

Study II focused on the comparison of the effectiveness of paper-based versus computer-based generative drawing on learning outcome, to determine whether students learn better when learning from science texts on paper or on the computer. Results showed a significant effect of the presentation medium on the learning outcome. Descriptive statistics showed hat students learned more when they read and generated drawings on paper than on a computer screen.

7) **Do students report higher perceived difficulty when they are asked to generate paper-based or computer-based drawings while learning from science text?**
   Study II further focused on students' cognitive load, particularly on perceived difficulty, again measured online (i.e., measured immediately after learning with a science text paragraph). In this study we wanted to determine whether students report more difficulties when they generated paper-based or computer-based drawings. Results indicated that perceived difficulty was significantly affected by the presentation medium. The descriptive statistics showed that students reported less perceived difficulty when working with the computer-based learning environment than with the paper-based learning environment.

8) **When do students report higher enthusiasm, difficulties with the mechanics of drawing, and challenges in metacognition and learning, when generating paper-based or when generating computer-based drawings?**
   To determine which factors and underlying aspects of the computer-based learning environment compared to the paper-based learning environment cause students' perception of difficulty, we developed a Medium Preference Questionnaire. Concerning enthusiasm, students reported to have significantly more fun to work with the computer. Additionally, students significantly preferred the computer as medium to work with in the future. Results concerning the issue of difficulties with the drawing mechanics showed that students say it was easier to generate drawings in the computer-based learning environment; thus there was a significant preference for the computer. In addition, students significantly preferred the computer as medium compared to paper choosing relevant elements from the toolbar. However, concerning the orientation of the given drawing elements, students indicated a significant preference for the paper-based material. Finally, results for the third issue, metacognition and learning challenges, showed that it was easier for students to correct their drawings and that they actually improved more of their drawings in the computer-based learning environment. Overall, students perceived it less difficult to generate drawings on the computer than on paper.

4.2 Empirical and Theoretical Implications

Some overall theoretical and empirical implications concerning (computer-based) generative drawing can be derived from the studies of this thesis and are discussed in the following.

The first main contribution of this thesis is that the generative drawing effect extends to a computer-based learning environment, because students learned better when they generated computer-based drawings while reading onscreen science texts than students who did not. This result is consistent with generative theories of learning (Mayer, 2009), which posit that people learn better when they engage in generative processing during learning. Generating computer-based drawings while reading a scientific text is intended to lead to an integration of verbal information, visual information, and prior knowledge. This generative cognitive processing leads to deeper understanding, according to the CTML (Mayer, 2009) and CLT (Sweller, Ayres, & Kalyuga, 2011). Overall, results of Study I show that asking learners to generate drawings of scientific texts using a computer-based tool fosters generative processing and is thus in line with previous studies (Schmeck et al., 2014; Schwamborn, Mayer, et al., 2010; Schwamborn, Thillmann, et al., 2010; van Meter & Garner, 2005). These studies showed the generative drawing effect when students are given instructional support while they draw by hand on paper. Further, the results of Study I provide an indication that the instructional support given in this study during the drawing process within the computer-based learning environment helped fostering generative processing, while at the same time it minimized extraneous processing caused by the mechanics of drawing.

The second main contribution is that there is a difference in students' learning outcome depending on whether students read and generate drawings on paper or on a computer screen. Results show that students learn more when they learn from a science text using the generative drawing strategy on paper (and drawing by hand) than on a computer screen (and drawing via drag-and-drop). Thus, there are differences in the effectiveness of computer-based and paper-based learning material. This result is consistent with assumptions derived from the generative drawing principle (Leutner & Schmeck, 2014; Schwamborn, Mayer, et al., 2010) and the first study of this thesis (see Study I, Chapter 2). Additionally, results concerning students' learning outcome are consistent with paper-based studies of generative drawing (Leopold & Leutner, 2012; Schmeck, 2010; Schwamborn, Mayer, Thillmann, Leopold, & Leutner, 2012; Schwamborn, Thillmann, Leopold, Sumfleth, & Leutner, 2010), as well as with findings from Leutner and Schmeck (2014) and partly with our Study I (Chapter 2). Although the generative drawing principle was extendable to computer-based learning in the first study of this thesis, the effect sizes of paper-based generative drawing on learning outcome were higher than the effect sizes of computer-based generative drawing on learning outcome. Thus, we carefully conclude that it does seem to matter which medium is used for the strategy of generative drawing.

The third main empirical contribution of this thesis is that the prognostic drawing principle can be generalized to computer-based learning, because students who produced high-accuracy drawings on a computer while reading science texts scored higher on learning outcome posttests than students who produced low-accuracy computer-based drawings (Study I, Chapter 2). Additionally, Study II showed that the drawing accuracy score for computer-based drawings (produced during computer-based learning) as well as for paper-based drawings (produced during paper-based learning) both correlate significantly with posttest scores related to computer-based paragraphs as well as to paper-based paragraphs. This is in line with the prognostic drawing principle coined and shown by previous research. The prognostic drawing principle proposed by Schwamborn, Mayer, et al. (2010) is based on the theory of generative drawing (van Meter, 2001; van Meter & Firetto, 2013; van Meter & Garner, 2005). This theory states that students who generate effective drawings, meaning drawings that are accurate regarding the learning content, build up a more coherent idea of the learning content and therefore construct meaningful learning outcomes. Besides generalizing the prognostic drawing principle to computer-based drawings, instead of replicating the prognostic drawing principle for paper-based drawing only, it is shown that the prognostic drawing principle seems to be independent of the medium students learn with.

Although our form of the computer-based drawing generation using the revised learning material from Schwamborn et al. (2011) and Schwamborn, Opfermann, Pfeiffer, Sandmann and Leutner (2012) appears to be successful at minimizing extraneous processing, as shown by the positive effect of computer-based drawing on the learning outcome in Study I, results also show that students reported higher cognitive load when they were asked to generate drawings. However, generative cognitive processes can be impeded by extraneous cognitive load caused by the instructional design, (e.g., the mechanics of generating drawings). When students perceive too much cognitive load, they usually have insufficient cognitive resources available for generative processing (Mayer, 2009). In Study I we found group differences concerning the perceived difficulty: Students in the generation groups reported perceiving higher difficulty, which is in line with studies of Leutner, Leopold, and Sumfleth (2009) and Schwamborn et al. (2011). Adding perceived difficulty ratings as a covariate (to statistically control for the effects of perceived difficulty on learning), served to preserve and strengthen the conclusion that computer-based drawing has positive effects on learning, by showing additional effects of generating drawings and higher effect sizes for the already shown effects. In other words, there are still differences between the groups after clearing for the covariate (here perceived difficulty) and results can not be ascribed to the covariate, anymore.

Contrary to the first computer-based study of Schwamborn et al. (2011), we found computer-based drawing to be an effective learning strategy (Study I). Further, our study revealed smaller effect sizes (for an overview see Leutner & Schmeck, 2014) concerning computer-based drawing on learning outcome (Study I) than studies using paper-based learning material (cf. Schmeck, 2010; Schwamborn, Mayer, et al., 2010; Schwamborn Thillmann, et al., 2010). However, computer-based drawing (see Study I and Schwamborn et al., 2011) as well as paper-based drawing (Schmeck et al., 2014; for an overview see Leutner & Schmeck, 2014) seem to increase students' cognitive load. Hence, in Study II we further investigated these findings by comparing computer-based and paper-based generative drawing directly.

Results of Study II demonstrate, on the one hand, that students reported perceiving significantly less difficulty when learning in the computer-based learning environment than in the paper-based learning environment. On the other hand, however, learning outcome tests showed significant differences between computer-based and paper-based generative drawing. As already mentioned students learned more when they read and generated drawings on paper than on a computer screen. The first result partly contradicts the assumption (Study I) that computer-based learning environments are still a bit too intrusive when using generative drawing. This assumption resulted from the finding that despite generating drawings is a successful learning strategy in computer-based learning environments students who generated visualizations reported more perceived difficulty than students who did not. Although the second result is partly in line with findings of our Study I and with the studies of Schmeck (2010), Schwamborn, Mayer, et al. (2010), and Schwamborn, Thillmann, et al. (2010), it seems to be inconsistent with the first result. As we combine these two results, it is obvious that they are not in line with the Cognitive Theory of Multimedia Learning (CTML; Mayer, 2009) and the Cognitive Load Theory (CLT; Chandler & Sweller, 1991; Sweller et al., 2011), which state that extraneous load, here measured by perceived difficulty, decreases cognitive capacity, which can lead to cognitive overload not leaving enough space for generative processing and thus learning. Surprisingly we found that students using paper-based generative learning score higher on learning outcome even though they reported to perceive more difficulty within this learning environment.

However, Study II investigated underlying aspects of students' perceived difficulty of drawing (using a Medium Preference Questionnaire), which can partly explain the contradictory results. Results of the Medium Preference Questionnaire (Study II) show that students reported to have significantly more fun to work with the computer and to prefer the computer as medium to work with in the future. Concerning the issue of difficulties with the drawing mechanics, results showed that students perceived generating drawings as well as choosing relevant elements from the toolbar in the computer-based learning environment easier. However, concerning the orientation of the given drawing elements, students indicated a significant preference for the paper-based material. Results for the third issue, metacognition and learning challenges, showed that it was easier for students to correct their drawings and that they actually improved more of their drawings in the computer-based learning environment. Thus, overall students stated that they perceived less difficulties within the computer-based learning environment (investigated by the Medium Preference Questionnaire), which supports the finding that students rated to perceive significantly less difficulty when learning in the computer-based learning environment than in the paper-based learning environment.

However, looking at the students' statements that it was easier to correct and improve their drawings in the computer-based environment, there is a risk of students not engaging in enough cognitive as well as metacognitve activities, i.e., students do not bother to think enough before drawing, because it is easy to delete and change the drawing elements, which might lead to not building a sufficient mental model and, as a consequence, fewer learning outcome. Besides being categorized as cognitive and metacognitve activities within our Medium Preference Questionnaire these two items could also be categorized as challenges with the mechanics of the drawing, thus as challenges with the instructional design of the learning environment that are related to extraneous cognitive load.

Some of these results could partly explain the mismatch between the higher perceived difficulty and the higher score on learning outcome for the paper-based learning environment. Nevertheless, with the strategy of generative drawing, our aim is to foster processes like metacognition (and as a result generative processing) to achieve deep understanding (Mayer, 2009) as well as learning. Additionally, generative theories of learning posit that people learn better when they engage in generative processing during learning, that is, cognitive activities aimed at making sense of the material (Mayer, 2009). In this study results according students' learning outcome showed that generative processing seems to be stronger for the paper-based material.

All results concerning the underlying aspects of difficulties and medium preference give important indications on how to organize and design learning environments for optimizing the learning strategy of generative drawing. In the field we want to have an effective learning medium that minimizes extraneous cognitive load while promoting germane cognitive load. Practical implications of the mentioned findings are reviewed in the next section.

4.3 Practical Implications

Several practical implications can be drawn from the two studies of the present thesis. First, results provided evidence for a generative drawing principle in computer-based learning environments, because we found that students learned better when they generate computer-based drawings while learning from an onscreen science text than students who did not generate drawings. However, in Study I we used a drawing prompt, a drag-and-drop mechanism and a pre-training, as support for drawing and to implement the drawing process with a method that reduces extraneous processing initiated by the instructional design. Based on our results, we recommend using generative drawing during computer-based learning with science texts, when drawing is supported in a way that extraneous load is reduced.

In addition to the generative drawing principle, we propose the prognostic drawing principle for computer-based learning. This thesis shows that the accuracy of the drawings students generate during learning predicts the quality of learning outcomes. This is true for paper-based drawings (Study II) as well as for computer-based drawings (Study I and Study II). Based on this, drawing accuracy could be used as formative assessment (Black & Wiliam, 2009): Teachers and students themselves get prompt feedback concerning the learning progress. Using generative drawing puts students in the position to use their drawings to monitor what they have understood from the learning information, enabling them to go back to the text if necessary. Additionally, teachers could use the accuracy of the drawings to adjust their instruction if necessary.

The extension of the generative drawing principle and the prognostic drawing principle to computer-based learning environments is especially important because computers gain constantly more attention within school education (Ross, Morrison, & Lowther, 2010).

Based on the results of Study I and II, it is important to take students' difficulties and preferences for the computer-based or paper-based learning environment into account when implementing the generative drawing strategy. When instructing students to draw during learning from science text, the aim is to foster generative processing (such as metacognition) to achieve better understanding (Mayer, 2009). In Study I we saw that this works within computer-based learning environments, but students perceived higher difficulty when generating drawings than students who did not. When comparing computer-based and paper-based generative drawing directly, there was a significant difference concerning the learning outcome, as students learned more when they read and generated drawings on paper than on a computer screen.

Looking at perceived difficulty in general (measured online by the item from (Kalyuga, Chandler, & Sweller, 1999) students perceived generating computer-based drawings as less difficult than paper-based ones (Study II, Chapter 3), although Study I showed that computer-based generation was still too demanding. However, looking at the underlying components of students' perceived difficulty (measured with a Medium Preference Questionnaire), we see the results on students' enthusiasm (closely linked to students' motivation) show students' preference for the computer. The same applies to the mechanics of drawing: Overall, students reported that it was easier for them to generate drawings on the computer than on paper, which can partially explain why students perceived less difficulty when generating computer-based drawings. Thus these results partly explain the inconsistency between higher perceived difficulty and at the same time a higher score on learning outcome for the paper-based learning environment.

Additional results of the Medium Preference Questionnaire give important advice about how to organize and design learning environments using the learning strategy of generative drawing. For example, people should take into account that although the drag-and-drop mechanism seems to be easier to handle than drawing by hand, this simultaneously increases the risk that students do not engage in enough metacognition, which can result in shallower generative processing and less deeper learning. Another specific problem of the computer-based learning environment used in our studies was that the orienting of the drawing elements was rated as more difficult when it was drag-and-drop. Additionally, this shows that drawing using drag-and-drop by means of a track pad or mouse is still not the same as using a pencil. However, results show that students have more fun and thus are more motivated to work with the computer material, but perform better when learning with the paper material. Consequentially, we propose a combination of paper-based text with on-screen drawing with mechanics that mimics drawing by hand. However, at the same time students should be able to see drawing elements and a drawing background, and they should have the opportunity to eliminate drawing elements quickly and easily. To combine benefits of both media, a tablet computer could be used. It is highly probable that this combination causes less extraneous load and at the same time fosters generative processing and thus meaningful learning (Mayer, 2009; Sweller, 1999, 2005).

4.4 Future Research and Conclusion

Based on the results of these two studies, future studies should further investigate several important aspects. First, our studies found evidence for the positive effect of generative drawing on learning outcome and also showed evidence for reinforced cognitive and metacognitive processes (see Medium Preference Questionnaire, Study II) in line with the Generative Theory of Drawing Construction (GTDC; van Meter & Garner, 2005; van Meter & Firetto, 2013). However, because our study was the first study showing this effect using computer-based drawing, further replications of this positive effect on learning would be important.

Second, as mentioned in the practical contributions section above, the drawing procedure based on drag-and-drop is not the same as using a pencil and thus students are probably not as familiar with computer-based drawing as with paper-pencil-based drawing. As a consequence, this procedure might be still a bit too intrusive, indicated by higher perceived difficulty ratings when generating drawings in Study I and higher learning outcomes within paper-based learning environments in Study II. Future work is needed to determine if the effects of the generative drawing principle can be strengthened when a combination of benefits of both computer-based and paper-based generative drawing is used. One particular focus could be to investigate how the usage of a tablet computer would impact the effect of generative drawing. Using a tablet computer would allow students to use a pencil-like tool but still work within a motivating computer-based environment, and the science content could also be presented as a paper-based text simultaneously. If benefits from both media are combined (i.e., less perceived difficulty and a higher learning outcome) and a more natural form of drawing is used, it is expected that extraneous processing will be minimized and students will have more cognitive resources available for deeper learning.

Third, by showing positive effects of generative drawing in computer-based learning environments (mainly Study I) this thesis indicates some efficacy of the drawing prompt (the toolbar showing all relevant pictorial elements and the partly pre-drawn background) as additional instructional support when learning with self-generated drawing. For a clarification of the efficacy of the drawing prompt, further studies should compare generative drawing with the drawing prompt, meaning with a variation of both elements of the drawing prompt (the toolbar and/or a partly pre-drawn background) and without any type of drawing support. Drawing without any type of drawing support (also possible when using a tablet computer) could help support students' creativity. Their creativity was restricted in this thesis, due to the provision of the toolbar and the partially drawn background. A greater freedom in drawing, which students have when they work with paper and pencil or on a tablet computer, could, on the one hand, become a source of extraneous processing for inexperienced learners. On the other hand, it could support their learning. In summary, further research concerning the role and the degree of guidance needed for computer-based as well as for paper-based self-generated drawings would also inform the development of more efficient and supportive learning environments.

Fourth, because students in our Study II who worked with paper-based and computer-based generative drawing stated that they perceived more difficulty in the paper-based environment, more studies should be conducted using the same design to replicate the results concerning cognitive load. Additionally, the inconsistent results concerning the higher learning outcome in contrast to higher perceived difficulty with paper-based drawing should be investigated once again. Thereby, it should also be investigated if *generative processing underutilization* (Mayer, 2009) could be the reason for the contradictory results. In other words, generating drawings in the computer-based learning environment may be easier and thus students have cognitive capacity available, but they do not choose to use it for making sense of the material.

It is important to mention that, in contrast to previous studies concerning the relationship between cognitive load and self-generated drawing (cf. Leutner et al., 2009; Schwamborn et al., 2011), in our studies we decided to measure cognitive load online, meaning immediately after working with each paragraph (e.g., Opfermann 2008; Paas & van Merriënboer, 1994) instead of only once after the whole learning task (e.g., Kühl, Scheiter, Gerjets, & Edelmann, 2011; Leutner et al., 2009; Schwamborn et al., 2011). We did this in accordance with research regarding the point of time when subjective rating scales for cognitive load measurement should be applied (van Gog, Kirschner, Kester, & Paas, 2012) and to differentiate the relationship between cognitive load and self-generated drawing more detailed (cf. DeLeeuw & Mayer, 2008). In Study II we measured cognitive load by means of only one item, namely the perceived difficulty item of Kalyuga et al. (1999), because we were especially interested in the extraneous cognitive load related to difficulties students have when creating drawings. We also opted to include only one item for the sake of parsimony. However, future studies using the same study design as in Study II should measure cognitive load by means of the item of Kalyuga et al. (1999) as well as by means of the item of Paas (1992), to be able to look at students' invested mental effort, as well. Extending this research is particularly important because, according to Paas, Tuovinen, Tabbers, and van Gerven (2003), mental effort refers to the cognitive capacity that is actually allocated to accommodate the demands imposed by the task; thus, it can be considered to reflect the actual cognitive load.

Additionally, extension is important because of findings of DeLeeuw and Mayer (2008). Results of their study showed, that mental effort ratings are most sensitive to manipulation of intrinsic processing, whereas difficulty ratings were most sensitive to indications of germane processing. Most sensitive to manipulation of extraneous processing, indeed, seems to be response time measurement, thus an objective measurement. Nevertheless, the items we used were self-report and subjective measurements, which can provide a useful substitute for some kinds of objective data (cf. Crockett, Schulenberg, & Petersen, 1987; Howard, 1994) but could also be criticized regarding assessing cognitive load with only single items (e.g., Brünken, Plass, & Leutner, 2003). Future studies should include more objective measures and not so heavily rely on self-reported measures as do the present studies. For example, different difficulties students have with the mechanics of drawing during learning from science text could be assessed through physiological measurement of cognitive load such as eye tracking (Van Gog & Jarodzka, 2013) or measuring brain activity (Paas, Ayres, & Pachman, 2008). Additionally, simple objective measures such as observer ratings of difficulties students have when drawing (e.g., whether students are daydreaming or make many corrections of their drawings) or response time could be used in future studies. To promote further research of cognitive load within generative drawing, more results of the subjective cognitive load measurements are necessary. On the one hand more results of the two items of Kaluya et al. (1999) and Paas (1992) are necessary to verify whether participants interpret the questions differently, e.g., in terms of extraneous cognitive load or as an overall impression of the load (Seufert, Jänen, & Brünken, 2007). On the other hand, more results of the Medium Preference Questionaire are necessary to be able to classify the questions dependable as extraneous load or germane cognitive load features (DeLeeuw & Mayer, 2008).

Fifth, although we did find positive effects of computer-based generative drawing on the learning outcome and therefore can carefully conclude that our instructional support given during the drawing process was successful, we did not find an effect of the order of the lessons (see Study I). The order in which the students worked with the science lessons (chemistry or biology) did not affect their performance in learning outcome posttests. The pretraining does not seem to have an effect on learning, which should be invested in future studies.

Further research using the study design of Study II should include a control group, such as in Study I in which the control group only read the science text and did not generate drawings. This would give the opportunity to compare the effect of computer-based as well as paper-based generative drawing with the effect of just reading the text and also to be able to take account of learning time.

Additionally, further research including follow-up scores is needed to determine if computer-based drawing can improve learning over time.

Finally, although in Study I one of the learning groups got the science text and provided pictures to learn with, we did not find the multimedia effect. Because we found that students in the multimedia group did not spend more time in the learning environment than students who did not have illustrations, we assume that they did not pay much attention to the given pictures, which might be the reason for not finding an effect of the given pictures.

Conclusion

Our research aimed to further explore the effects of computer-based generative drawing, that is, whether positive learning effects of this strategy can be generalized from paper-based to computer-based learning environments. We also investigated whether an extension of the prognostic drawing principle to computer-based learning is possible. Finally, we compared computer-based and paper-based generative drawing and aimed to investigate specific underlying difficulties, challenges, and motivational aspects of both learning environments. Results show that the generative drawing principle as well as the prognostic drawing principle can be generalized to computer-based learning. Thus, it does matter in which medium students work with help of this strategy. However, learning outcome in the paper-based learning environment is higher than learning-outcome in the computer-based environment. Looking at cognitive load and underlying aspects of the instructional design, we found promising starting points for further research as well as for the implementation of generative drawing into everyday school life. Based on the results of this thesis the primary aim of future research should be the extension of theoretical and empirical embedding of the generative drawing strategy. The experiences of students during drawing that are described in this thesis should be used to improve learning environments and to derive design principles in future research. Finally, benefits of both media should be combined in using a tablet computer to generalize our findings to more innovative and user-friendly media.

4.5 References

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