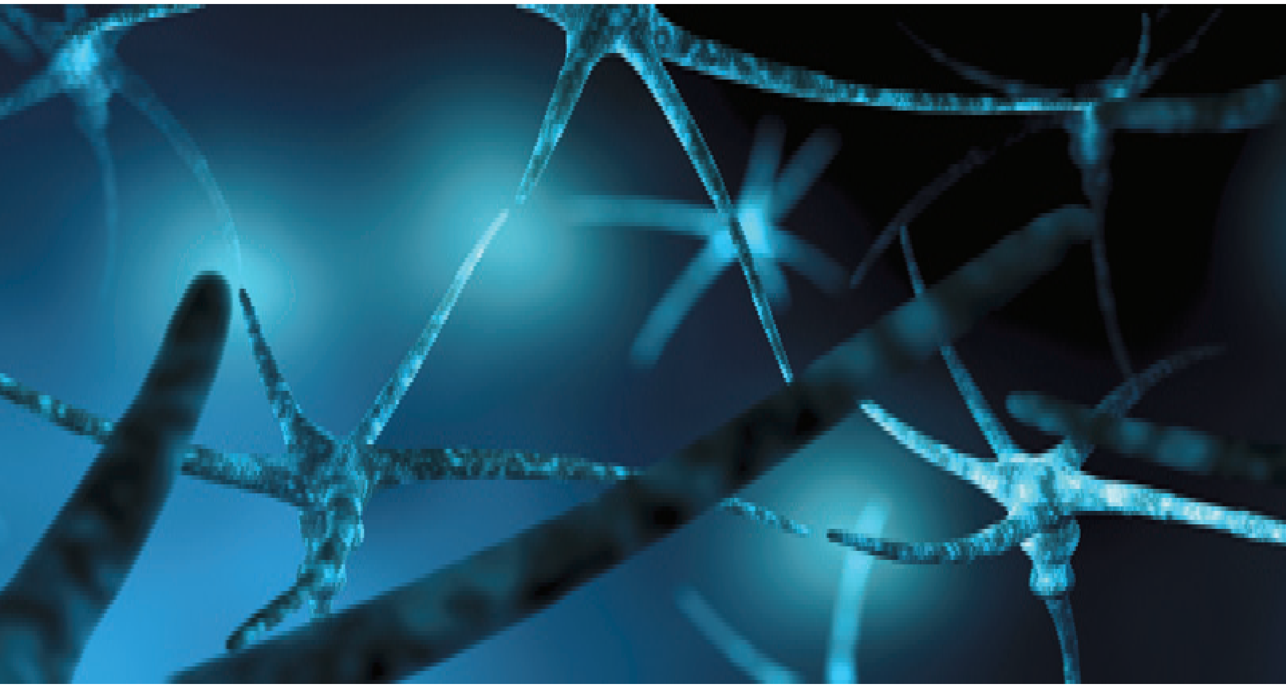
Planning with Graphical Overviews

Effects of Support Tools on Self-Regulated Learning



Wilco J. Bonestroo

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PLANNING WITH GRAPHICAL OVERVIEWS

EFFECTS OF SUPPORT TOOLS ON SELF-REGULATED LEARNING

PROEFSCHRIFT

ter verkrijging van
de graad van doctor aan de Universiteit Twente,
op gezag van de rector magnificus,
prof. dr. H. Brinksma,
volgens besluit van het College voor Promoties
in het openbaar te verdedigen
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"The real revenge is not what we do intentionally against one another. It is the tendency of the world around us to get even, to twist our cleverness against us. Or it is the own unconscious twisting against ourselves. Either way, wherever we turn we face the ironic unintended consequences of mechanical, chemical, biological, and medical ingenuity – revenge effects, they might be called."

Edward Tenner
Why Things Bite Back: Technology and the Revenge of Unintended Consequences

Chapter 1

General Introduction

Abstract

In this chapter, we introduce the topics associated with the main subject of this dissertation: planning with graphical overviews. The chapter starts with the recent developments in technology and education that gave rise to the research project in which the studies described in this dissertation were performed. The key elements that are used throughout the dissertation are defined in terms of the current literature on technology-enhanced learning and self-regulated learning. The chapter concludes with the formulation of the research questions that are addressed in this work and with a general outline of the dissertation.

1.1 Introduction

Planning is an essential part of the learning process. It involves strategic thinking about which steps to take in the oncoming learning process. Planning is performed as one of the first activities in the whole process and, therefore, can potentially influence the subsequent activities in that process. Because planning requires pedagogical knowledge and knowledge about the learning domain that is to be learned, it can be difficult for individual learners to plan their own learning process without help of others. The studies described in this dissertation address the use of software tools to support such planning processes. This chapter sets out with a description of two developments in technology and education that emphasized the importance of planning and gave rise to the studies described in this dissertation and the overarching project in which these studies were performed. The following sections describe recent developments in information distribution and the consequences for learning, and the observed shift towards self-directed learning (SDL).

New Ways of Distributing Information

We live in a knowledge-based economy and society, in which the creation, the use, the distribution, and the management of knowledge are becoming more and more important (Harris, 2001). To acquire knowledge, we process and transform information in an activity we all know as learning. Therefore, having access to appropriate information is essential for learning. The ongoing developments in ICT have not only changed the way information is stored, but also the way information is distributed. Especially the rise of the World Wide Web (WWW) has led to an immense growth of accessible digital information that can potentially be used for learning. Traditional learning resources, such as instructional books or educational courses, nowadays have to compete with millions and millions of digital resources ranging from static web sites to dynamic and interactive learning objects available on the web. These new resources free us from traditional constraints such as time and space, as they are always easily and freely accessible from any computer with an internet connection. However, because anybody can put information on the web, there is absolutely no guarantee that information in those resources is correct. Ciolek (1996) observed a remarkable difference between the quality and structure of traditional instructional material compared to these new digital resources. Instructional material is professionally edited and designed in such a way that it stimulates and optimizes the learning process and is based on many years of research on education and instruction (e.g., Branch, 2009; Smith & Ragan, 1999). The first introductory chapters motivate learners, gain their interest about the topic, and prepare them for the upcoming learning process by activating prior knowledge and addressing basic and prerequisite knowledge for the following material. Thus, the first few chapters lay down a knowledge base on which the more complex contents of the subsequent chapters can be built. Moreover, the learning material contains exercises and example problems, so that learners can immediately apply and test their newly acquired knowledge. Digital resources, on the other hand, often are not intended to be used as instructional material and, accordingly, lack the profound structure found in instructional material. Moreover, digital resources are typically not as comprehensive as books and to cover a complete learning subject, multiple resources are required. Such fragmented resources are typically not intended to be accessed in a particular order and the learner has to decide in what order to work through such material. For example, current web browser technologies allow learners to navigate through resources by following hyperlinks that take them to another place in the current resource or to another resource. Information on the web is not only more disordered and fragmented, there is also an almost infinite amount of information directly available. In contrast to instructional books, digital resources are never finished; there are always more hyperlinks that take learners to related material. Learning effectively and efficiently from such digital resources obviously requires different skills compared to learning from more traditional resources. Yorke (1999) observed a similar fragmentation in higher education which he called "unitization of curricula", which means that curricula and courses are split up in smaller units and that students have to plan their learning based on these small units. Learners have to make instructional decisions and have to pull the pieces of information from several resources together into one coherent and integrated knowledge structure. In his book, Yorke warned that students need more guidance to navigate through such unitized curricula.

Developments in ICT have not only led to the availability of more and different types of information, they have also enabled us to process this information in a smarter way. One big advantage of computer technology is that computers can help us to search, filter, and order available information. Moreover, computers can automatically adapt that information to the needs of the learner. Using such adapted material for learning could lead to better learning results, compared to using fixed, unchangeable learning material. In educational technology, the term computer-based learning environment (CBLE) refers to the use of computer technology and software to support learning (Winters, Greene, & Costich, 2008). A CBLE is a computer program that can contain learning resources, ranging from static documents to interactive simulations of the learning domain, and that can perform the actions described above. The last decade has shown a spectacular growth of CBLEs that are so sophisticated that they can take over some of the teachers' tasks, such as the selection of appropriate learning goals, learning strategies, learning plans, and learning material. Based on the information that such systems have about the learner, the learning goals, and the learning domain, they are able to generate courses tailored to the individual learner. The advantage of such systems is that once they are developed, they can be applied on a large scale without much human intervention. As such, these developments allow for an individual approach in learning, without the costs of a personal teacher. Computers have become ubiquitous in our society and these systems have become available for nearly everyone. Research on CBLEs often focuses on the technical features, such as intelligent algorithms aimed to support the learning process and the contents and structure of the computational models. For educational purposes, however, we are especially interested in the effects of such environments on learning.

Although many have praised the features and benefits of these new technologies, there are also concerns about the effects of such intelligent learning environments on the learning process. For sure, CBLEs have an influence on cognitive processes that learners perform during learning, and, therefore, CBLEs potentially influence learning outcomes. It is not the question whether cognitive processes are changed by applying technology; it is the question what the effects of those changes on the learning process are.

Self-Regulated Learning

In recent years, learners in the Dutch educational system more and more have become responsible for their own learning process. Nowadays, pupils and students are in a great part expected to regulate their learning processes. This trend is not only seen in education, but also at the workplace, where more and more knowledge workers have become responsible for their learning questions throughout their whole career (e.g. Pepin, 2007; Sociaal Economische Raad, 2002). This shift in responsibilities has drastically changed learners' tasks and roles. Traditionally, instructional decisions, such as the selection of learning goals and learning material, were made by teachers, instructional designers, or by subject matter experts. However, when learners regulate their own learning, they must perform all such tasks themselves, besides performing the actual learning task. In the literature on educational research, there are two similar terms that describe learning in which learners exercise control over their own learning: self-directed learning (SDL) and self-regulated learning (SRL). Both forms of learning have gained much research attention (e.g., Candy, 2004; Puustinen & Pulkkinnen, 2001; Simons, 2000; Winters, et al., 2008; Zimmerman, 2002). Although SDL and SRL are similar terms, there is a subtle difference between them. SDL is commonly associated with adult education, and Knowles (1975) defined it as "a process in which individuals take the initiative, with or without the help from others, in diagnosing their learning needs, formulating goals, identifying human and material resources, choosing and implementing appropriate learning strategies, and evaluating learning outcomes" (p. 19). The key point in SDL is that individuals take the initiative for learning. In SDL, the learning task is always defined by the learner. In SRL, however, the focus is not on the initiative for learning, but on the subsequent steps in the learning process (Loyens, Magda, & Rikers, 2008). SRL covers the whole learning process and all tasks performed within that process. In this dissertation SRL is used as the theoretical framework, because it allows to examine the learning process in more detail than SDL. An important assumption of SRL is that learners do not passively consume presented learning material, but they take a proactive approach to the learning process. Research has shown that SRL is commonly associated with academic achievement and success, but also that SRL is difficult to master (Zimmerman & Schunk, 2001). SRL is a broad concept, covering all aspects of the learning process. To examine SRL, several authors have developed models to capture and identify all these aspects. Accordingly, there are now several different models of SRL. In a comparison of the five most well-known models, Puustinen and Pulkkinen (2001) identified three main phases in the learning process that were globally present in all models: the preparatory, the performance, and the appraisal phase.

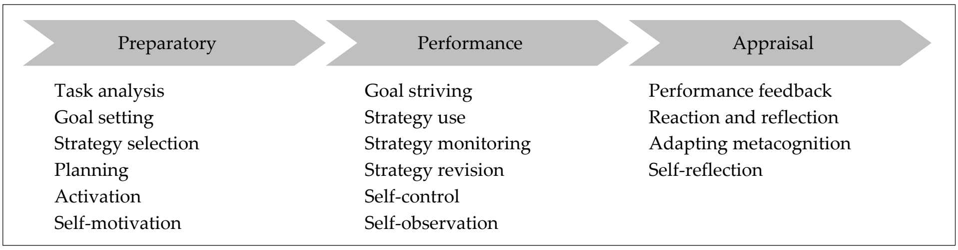

Figure 1. Schematic overview of self-regulated learning processes. Based on: analysis performed by Puustinen and Pulkkinen (2001).

These three phases are graphically represented in Figure 1. The figure shows the three identified phases and, for each phase, lists activities that are typically performed within that phase. In this dissertation, we examine the effects of planning, an activity performed in the first phase, on other activities in the whole process and on the actual learning outcomes. To understand the relationship between all involved aspects, we needed a more fine-grained description of SRL than the description shown in Figure 1. From the five models examined by Puustinen and Pulkkinen, we identified Winne and Hadwin's SRL model (1998) as the most appropriate theoretical framework for our research. Their comprehensive model is an extension of Pintrich's model, which was grounded on information processing theory (IPT). According to IPT, humans can be modelled as computer systems that take in information, process that information in short-term memory, store information to and retrieve information from long-term memory, etc. An important assumption in IPT is that the minds of learners, and especially their short-term memory, have a limited capacity. If a task, such as learning, exceeds that capacity, the task cannot be performed successfully and learning is hampered (Chandler & Sweller 1991; Sweller 1988, 1989; Sweller et al. 1990). Winne and Hadwin's model extends the IPT model but also includes aspects, such as contextual, cognitive, and motivational aspects, and explicitly identifies activities performed in the learning process.

According to Winne and Hadwin's model, SRL takes place in four phases: 1) task definition, 2) goal setting and planning, 3) studying tactics, and 4) adaptations to metacognition. A graphical representation of their model with the four learning phases and the dependencies between them is shown in Figure 2. In each phase, learners can perform information processing activities and such activities can result in concrete products, such as learning plans, or in cognitive products, such as knowledge about the learning material. Winne and Hadwin used the term operations to describe such activities. In their model, conditions determine which operations are performed in a certain phase. Conditions can be external to the learner, such as the availability of learning material or features of the used CBLE. However, conditions can also be internal to learners, such as the learners' motivation and their SRL skills. During evaluation, learners compare their current performance or knowledge to their standards. In SRL, learners are expected to evaluate their learning. Evaluation can be performed during or after the learning process. If evaluations are performed during learning, they can be directly used to change the current learning strategies that learners employ. Winne and Hadwin described their model as a recursive, weakly sequenced system. *Recursive* means that the four identified phases can be traversed repeatedly and that there can be dependencies between the phases. For example, products from one phase (e.g., learning plans in phase 2) can influence conditions and operations of another phase (studying tactics in phase 3). With *weakly sequenced* they mean that although learners can move back and forth through the four identified phases, learners generally proceed from phase 1 to 2 to 3 and optionally to phase 4.

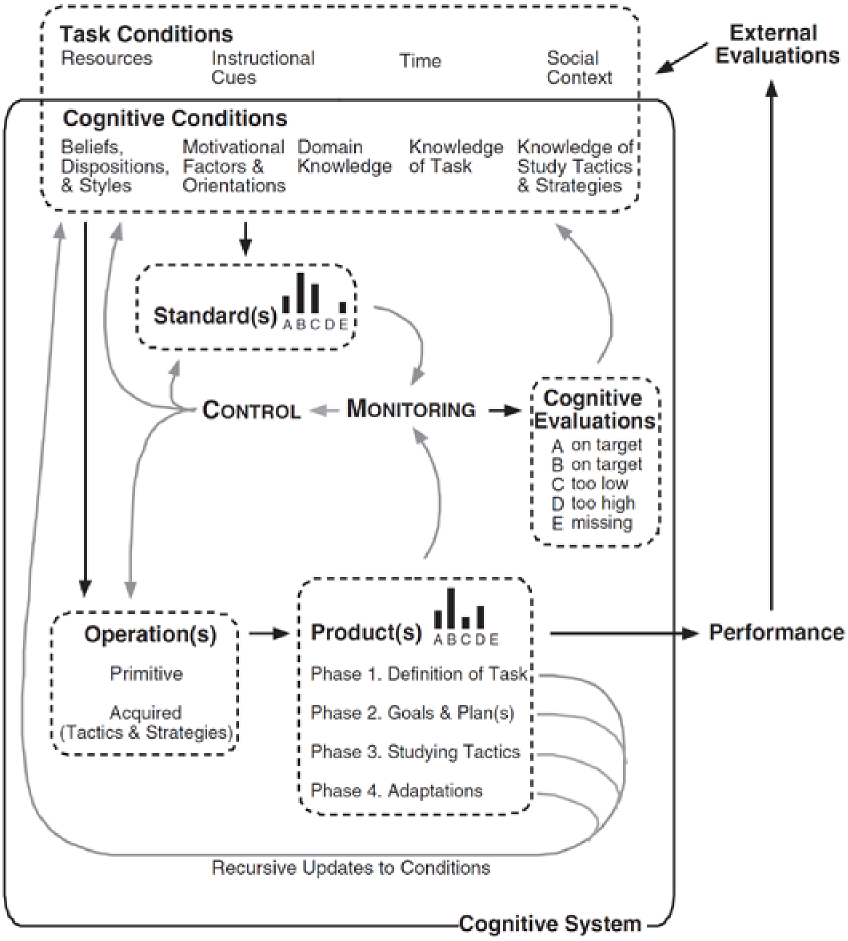

Figure 2. Graphical representation of the Winne and Hadwin's model of SRL. Source: Zimmerman & Schunk (2001).

The shift towards SRL has made learners more responsible for their own learning. Moreover, the developments in ICT described above, especially the new ways of distributing information, require a different approach to the learning process. The abundance of fragmented information sources makes it more difficult to learn from such sources compared to learning from traditional learning materials. The research documented in this dissertation was performed within a project that developed a CBLE to support learners to learn from sources that were originally not developed as learning material: the APOSDLE project (www.aposdle.org). In this section, we give a brief description of the project and in Chapter 2 the project is described in more detail. APOSDLE focussed on learning at the workplace and the underlying assumption was that a considerable amount of information is digitally available in the computer networks of companies. However, learning from such information sources can be difficult, because the sources are often difficult to find and not optimally structured for learning. According to the classification put forward by Bransford (2000), the APOSDLE software is a mixture of a knowledge-centred and a learner-centred learning environment. Like in similar systems, APOSDLE relies on learning domain models to store knowledge about the learning domain, and user models to store knowledge about the users of the system. These models, combined with instructional rules, enable the system to make sense of existing resources and filter them to match the knowledge levels and eventual learning goals of the learners. APOSDLE's software aimed to help learners by searching relevant information, and help the learners to make a structured learning plan. The system could even compose complete learning objects with plans based on the existing sources. However, it was the question whether such an approach would be actually beneficial for learning, because taking over learners' cognitive activities influences their learning process and this could influence learning outcomes. In this work, we examine the effects of actively planning on learning. With the information from these studies we want to be able to design more effective and efficient learning environments.

1.2 What is Planning?

This dissertation focuses on one of the first activities in the SRL process: the planning of learning. As there are many interpretations of the concept of planning, this section describes how planning was interpreted in this dissertation. Intuitively, planning includes deciding what to do, in what order, and when to do it. In their work on plans and behaviour, Miller, Galanter, and Pribham (1960) defined plans as "any hierarchical process in the organism that can control the order in which a sequence of operations is to be performed" (p. 16). In line with the ideas of IPT, the authors described that a plan for an organism is similar to a program for a computer. The plan controls the sequence of performed operations. To distinguish planning from other activities in SRL, Azevedo, Guthrie, and Seibert (2004) developed a coding scheme in which they described that "[a] plan involves coordinating the selection of operators" (p. 292). These operators refer to the information processing activities described in Winne and Hadwin's SRL model. According to these two definitions, planning is still a broad concept that addresses the selection of actions and the order in which those actions are executed. According to Winne and Hadwin's model, there is a distinction between goal setting and planning. Goal setting is the determination of the learning goals that one wants to achieve. During planning, learners decide *how* to reach those learning goals. This distinction allows us to control one aspect of the goal setting and planning phase and letting the other free. For example, learning environments can determine learning goals, while learners create the plans, or learners can select learning goals, and the CBLE can generate the corresponding plans. When planning is supported or restricted by the CBLE, this influences the task conditions. In the following section, we first describe different variants of planning and then we describe how planning was defined in the current study.

Types of Planning

In learning, plans can cover concise learning sessions but they can also cover a whole curriculum, spanning multiple years. Plans can also vary in the amount of detail. This can range from abstract plans in which only the outline of the learning program is sketched to detailed plans in which all elements are completely described. In planning the learning process, learners can plan what type of actions they are going to perform, e.g., read, rehearse, practise, etc. In teacher education, teachers are taught to develop comprehensive lesson plans. In a lesson plan, teachers write down what they are going to do (the activities and processes) and what topics they are going to teach (the contents) in a particular lesson. Based on the objectives of the lesson, teachers decide on the learning material. Such lesson plans include several types of concepts, such as learning goals, learning material, instructional actions, and questions. However, planning can also be more restricted, for example when only the order of the contents in determined. It is assumed that planning is more difficult when learners have to make decisions on both the processes and the contents, compared to when learners only have to decide on the contents. In daily use, planning generally also includes practical aspects such as available learning material, place, and time. When planning is performed on a computer, for example within a CBLE, the computer can support or even take over the planning process. To describe this aspect of control over the planning process, we use terminology from learner control literature. Merril (1984) identified several types of learner control: content control, sequence control, control of pace, display control, and control of internal processing. In her review, Lunts (2002) identified three types of learner control: content control, sequence control, and advisory control. Content control concerns the amount of control learners have over the contents of learning material. If the computer decides what content to use, we speak of program control. When the learner decides what content to use, we speak of learner control. The amount of control should be interpreted as a scale, with on the one end learner control and on the other program control. Sequence control is similar to content control, but it concerns only the order in which the learning material is accessed. Display control concerns what type of material to show for a certain topic. For example, learners can use definitions, detailed explanations, worked out examples, or exercises to learn a certain topic. When learners can decide what type of material to use, they are said to have display control.

We can now describe how planning was interpreted in this dissertation. In the tools used in the first study, learners had content control and display control over the learning process. Planning was not explicitly performed in these tools, but the tools visualized the learning domains to support learners to make instructional decisions. The planning tools that were used in the second and third study described in this dissertation aimed at planning concise learning sessions for individual learners. Learning plans were defined as sequences of topics from the learning domain. The tools presented the learning material in the order that was described in the learning plan. Accordingly, learners had sequence control. Because the learning domain contained instructional information about prerequisite relationships between topics, the tools could check whether all topics that were required for a learning plan were included in the plan. Although participants were free to edit their plans the way they liked, the tools only approved learning plans that adhered to the instructional information in the learning domains. This entailed that all used learning plans contained the same topics and that learners had sequence control, but they did not have content control. Moreover, the learning environment selected what (type of) material to show for every topic. Thus, learners did not have display control in the learning environment.

Research on Planning in SRL

Although many aspects of SRL are studied, there is remarkably little research on the effects of planning on learning. Because planning takes place in the first phase of learning, it has the potential to influence the whole learning process (either positively or negatively). Azevedo and colleagues (2004) studied SRL and in their work, they described that their “[…] results highlight forethought/planning/activation as a critical phase of SRL, and are in accordance with other SRL models that highlight planning as a prominent phase” (p. 106). Planning and the reorganization of learning material are assumed to have positive effects on learning, however, not all learners perform such processes spontaneously. Previous research shows that there are several ways to stimulate planning. Azevedo, Moos, Green, Winters, and Cromly (2008) provided students with a human tutor who facilitated self-regulative learning. They found that students performed more planning activities when they were supported by the tutor. Moos and Azevedo performed two studies in which students were provided with conceptual scaffolds (2008a, 2008b). Conceptual scaffolds were guiding questions that were expected to help learners to understand the relationship between different concepts in the learning domain. In both of their studies, they found that participants who received scaffolds performed more planning activities than participants who did not receive them. This corresponds with the results from Manlove, Lazonder and de Jong (2009), who performed three studies in which they provided learners with a support tool called the process coordinator. This tool contained goal-lists, hints, prompts, cues, and templates to support cognitive regulation for a modelling task. They also found that students performed significantly more planning activities with the tool than without it.

In the previous section, we identified a relationship between types of planning and types of learner control. When learners plan their own learning, they have more learner control over their learning, compared to when such plans are provided to them. Scheiter and Gerjets (2007) studied the relationship between learner control and motivation and found that learners who had more control over their learning environment were more motivated and interested. Cordova and Lepper (1996) found that even students who only received control over irrelevant parts of their learning environment not only showed increased motivation, but also learned more in a fixed time period. In addition, their depth of engagement, perceived competence and levels of aspiration increased. Swaak and de Jong (2001) compared the effects of tools in which they varied the amount of freedom given to the learners. Their results indicate that participants with more learner control had the same amount of definitional knowledge, but had significantly more intuitive knowledge. They found no differences in the interaction processes, in cognitive load, or in subjective ratings. However, several authors have noted that increased learner control together with non-linear learning environments could lead to problems such as disorientation and cognitive overload (e.g., Scheiter & Gerjets, 2007; Shapiro, 2008). Scheiter and Gerjets (2007) summarized findings from several studies and claimed that especially learners with low prior knowledge or with low metacognitive skills encountered such difficulties. They said that hypermedia is beneficial for learners with "positive cognitive styles and attitudes towards learning" (p. 293) and that high levels of learner control should only be used for learners with high metacognitive skills. To prevent learners from problems such as disorientation and cognitive overload, learner control can be reduced, for example by letting software make decisions for them. In her literature study on the effectiveness of learner control on computer-assisted instruction, Lunts (2002) demonstrated that the literature on learner control offered contradicting findings. She concluded that "there are no right answers on whether LC is beneficial for students and whether a higher degree of LC implied in a computer program improves instructional effectiveness" (p. 68). This is in line with the findings from Clarebout and Elen (2009), who concluded that current research does not demonstrate a clear relation between learner control and increased performance.

The studies described above show a clear relation between the provision of support tools and the number of planning activities. The effect of support tools on learning outcomes, however, is less clear. In one of the studies described above, learning outcomes were not measured at all (Moos & Azevedo, 2008a). In the other study, positive correlations were reported between the number of planning activities and knowledge (Moos & Azevedo, 2008b). Manlove, Lazonder and de Jong (2009) reported no relation between tool use and learning outcomes in two of their studies and a negative relation between tool use and learning outcomes in one of them. These findings show that although planning is generally considered an important part of the preparatory phase of the learning process with the potential to influence the performance and appraisal phase, research findings on the effects of planning on learning outcomes are mixed. Empirical studies show that different types of planning lead to different results.

1.3 Visualizations to Support Planning

To support planning, we visualized the structure of the learning domain with graphical overviews. Graphical overviews are assumed to provide insight in the structure of learning domains. There are several ways to represent such structural information, for example, graphic organizers (Winn, 1991), concept maps (Novak & Cañas, 2006), knowledge maps (O'Donnell, Dansereau, & Hall, 2002), and topic maps (Dicheva & Dichev, 2006). In all these types of graphical overviews, concepts are visualized as labelled nodes and relationships between concepts are visualized as lines or arrows between the nodes. Figure 3 shows an example of a graphical overview on the subject matter of errors in test statistics.

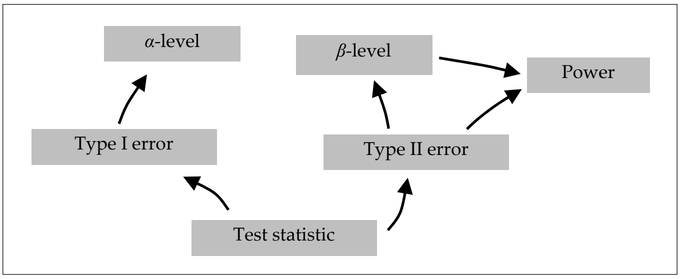

Figure 3. Example of a conceptual graphical overview showing topics and relationships between topics.

The rationale of using graphical overviews is that graphical displays can facilitate learning (Vekiri, 2002). Previous research shows that, in general, graphical overviews have a positive effect on learning. For example, Nesbit and Adesope performed a meta-study based on 55 studies and they found that across all studies "the use of concept maps was associated with increased knowledge retention" (2006, p. 413). Chen and Rada (1996) also performed a meta-study and they concluded that "graphical maps that visualize the organization of hypertext have significant impact on the usefulness of a hypertext system" (p. 125). Research also shows that visual characteristics influence how users interact with a graphical overview. For example, de Jong and van der Hulst (2002) found that the visual structure of graphical overviews and the provision of hints could guide learners through a learning domain, resulting in more domain-related exploration patterns.

However, not all studies on graphical overviews found positive effects. Some studies found no differences between the learning outcomes with graphical overviews and other forms of outlines. There are even studies that found a negative influence of the use of graphical overviews on the learning process. One possible explanation of the negative effects of using graphical overviews is that it is more demanding to navigate non-linear structures then linear structures. For learners who find the learning material difficult, the addition of an extra navigation task might cause their cognitive system to be overloaded, resulting in lower learning outcomes. A detailed discussion of the research on graphical overviews is included in Chapter 3.

To overcome such problems with graphical overviews, we added guiding information to the graphical overview: prerequisite relationships. A topic is prerequisite for another topic if it must be learned and understood before the other topic can be learned. For example, in introductory statistics one must first understand how to determine the *mean*, before understanding how to determine the *standard deviation*. All prerequisite relations together indicate how learners can best traverse the learning domain. For example, learners should first address *mean* and then address *standard deviation*. Several instructional and learning theories are based on this idea of conceptual, logical, or instructional prerequisites, such as Ausubel's Subsumption Theory (Ausubel, Novak, & Hanesian, 1978) and Reighluth's Elaboration Theory (Reigeluth, 1992). To support planning and sequencing we examined tools that helped to gain insight in the structure of the learning domain and the prerequisite structure, and helped to plan the learning process. By showing the high-level structure of the learning domain, we expected that learners would follow a more logical order through the learning domain and constructed well-organized bodies of knowledge. We think that the visualization used in our studies also helped to gain understanding in how the system worked. Participants could see the relationships that were used in the automatic reasoning of the tools. A recent study performed by Bolman et al. (2007) showed that participants had a strong need to understand how their tools worked. Learners wanted to have insight in what information was used by the automatic tool and how the tool came to the advice. The requirements, constraints, and conceptual designs for the tools used in this research are presented in the next chapter.

1.4 Research Questions

The research described in this dissertation was a design study, based on the ADDIE approach to instructional design (Branch, 2009). With ADDIE, there are five phases in the instructional design process: Analysis, Design, Development, Implementation, and Evaluation. During this whole project we performed three ADDIE iterations, in which results and findings from the previous iteration were fed into the following iteration. In each iteration we performed a study. We set out this research project with the aim to support planning and self-regulated learning by visualizing instructional information. In the first iteration, and corresponding study, the main focus was on the effects of visualizing the structure of the learning domain and the instructional prerequisite information. We performed a study in which we addressed the problem of disorientation in graphical overviews. This study is described in Chapter 3. Based on the literature on self-regulated learning, problem solving and knowledge visualization, we developed a tool to visualize the learning domain as a graphical overview. We tested whether a version of the tool that was enhanced with the visualization of instructional prerequisite relations would lead to more structured navigation, task performance and knowledge. The question we addressed in the first experiment was:

Question 1. *Does the visualization of prerequisites in graphical overviews guide navigation through the learning domain and does it lead to better task performance and more knowledge?*

In the first study, we asked participants to solve problems, while they could use our tool as a support tool. The tasks were constructed in such a way that participants had to search for additional information to perform the given tasks correctly. The learning material was organized so that participants would have to consult several resources in a logical order. Based on the outcomes of the exploratory phase, we stated the following research question:

Question 2. *Do learners learn more when they are actively involved in the planning process, compared to when they are provided with automatically generated plans?*

The second and third studies were performed to answer this question. In these studies, the concept of planning was explicitly added to the tool. The studies are described in Chapters 4 and 5. To test whether active planning with this tool would lead to more knowledge, we compared the effects of active planning on navigational behaviour, task load, and knowledge to the control condition in which learners were not actively involved in planning. When participants actively planned their learning process, they used the tool to construct a learning plan manually. To support this process, the tool provided a graphical overview with the instructional prerequisite information. In the control condition, the tool automatically created a learning plan and provided the resulting plans to the learners. We expected that manually creating a learning plan would lead to more structural knowledge, because participants would be cognitive active with the high-level concepts of the learning domain.

To test whether the findings from the second study were also applicable to the whole learning process, we integrated the tool from the second study in a learning environment with actual learning material. With this setup, participants could not only plan their process, but also perform the subsequent learning processes, based on the created plan. In the experimental condition, learners actively created plans. In the control condition they were provided with automatically generated plans. After planning, either performed by the participant or by the tool, the learning material was ordered according to the plan and presented to the user. This way, we could study the effects of actively planning learning material sequences on the whole learning process.

1.5 Dissertation Outline

Chapter 2 addresses the analysis, design, and development phase of the ADDIE process. In that chapter, we describe the requirements and constraint we had during the project and we provide the conceptual designs of the tools used in the studies.

The main part of this dissertation describes three experimental studies. The studies are described in a chronological order in Chapters 3, 4, and 5. These chapters are based on the journal manuscripts of the studies, and accordingly, each chapter is treated as a stand-alone chapter, that can be read independently, without knowledge of the other studies. Chapter 3 addresses the effects of adding visual prerequisite information to graphical overviews. The study examined a form of implicit planning, by analysing the paths learners took through the learning domain. We examined whether a visual representation of prerequisites in a graphical overview helped learners to navigate in a more domain related way, but also whether it helped to improve task performance and knowledge.

Chapter 4 describes the second study in which we focused on active planning. Based on the findings from the first experiment, we developed tools in which the focus was explicitly on the planning process. In the study, the effects of two tools were compared. The computer-generated (CG) tool created learning plans automatically an was used in the control condition. In the experimental condition, participants worked with the learner-generated (LG) tool. With that tool, learners manually constructed learning plans themselves. Both tools used the graphical overview with prerequisite information that was examined in the first experiment, and we studied whether active construction of a plan supported the learning process, compared to passive construction.

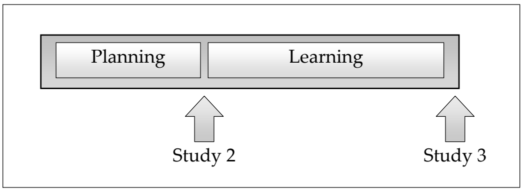

Figure 4. Moments of measurement for studies 2 and 3.

The third study is described in Chapter 5 and is a follow-up of the study in Chapter 4. We examined whether the findings of the second study were also applicable when the created plan was actually used in the learning process. The planning support tool was now integrated in a learning environment with learning material. We studied whether the effects found in the previous study positively influenced the whole learning process.

The findings from the three studies are combined in Chapter 6. First, the individual results from the three studies are described and compared. Then, the results are put together to draw conclusions about what we have learned about the planning process in CBLEs. The final chapter of this dissertation contains the Dutch summary of this work.

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Chapter 2

Requirements, Guidelines, and Conceptual Design of the Tools

Abstract
In this work, we examine the effects of support tools on the learning process. The guidelines for the examined tools came from the literature on technology-enhanced learning (TEL) and self-regulated learning (SRL). The requirements came from the overarching project in which these studies were performed: the APOSDLE project. This chapter sets out with a description of the APOSDLE project. We provide an overview of the objectives of the project, of the envisioned approach to reach those objectives, and of important aspects of the underlying software architecture of the system. The requirements from the project were combined with the guidelines from TEL and SRL literature to guide the design of the tools that we examined. This chapter concludes with the description of the conceptual designs of our tools.

2

2.1 Introduction

The studies described in this dissertation were performed in the context of the APOSDLE project. The APOSDLE project provided several requirements on the tools we developed in this research. Those requirements, combined with current understanding of self-directed learning and technology-enhanced learning, determined the direction of the performed studies and the development of the learning tools. The aim of this chapter is to provide insight into the rationale for the design decisions made during this research project and to present the resulting conceptual designs of the tools used in our studies.

2.2 The APOSDLE Project

APOSDLE was an integrated project that was funded by the European Commission's Sixth Framework Programme. APOSDLE is an acronym and stands for Advanced Process-Oriented Self-Directed Learning Environment. The project started in 2006 and was completed in 2010. The University of Twente was one of the twelve partners participating in the project. Besides research partners, there were technical partners and application partners involved in the project. The technical partners were responsible for developing the software and technologies. The software was tested at the application partners. The overall goal of APOSDLE was to study and develop integrated ICT support for knowledge workers at their workplace. The basic idea was that knowledge workers fulfil different roles in their organizations: the role of worker, expert, and learner. To allow knowledge workers to conveniently switch between those roles, APOSDLE aimed to provide one comprehensive software environment in which these three roles were combined. The research described in this dissertation addresses the role of the learner and tools to support this role. APOSDLE's general objective with regard to learner support, documented in the project's description of work (DOW), was formulated as follows:

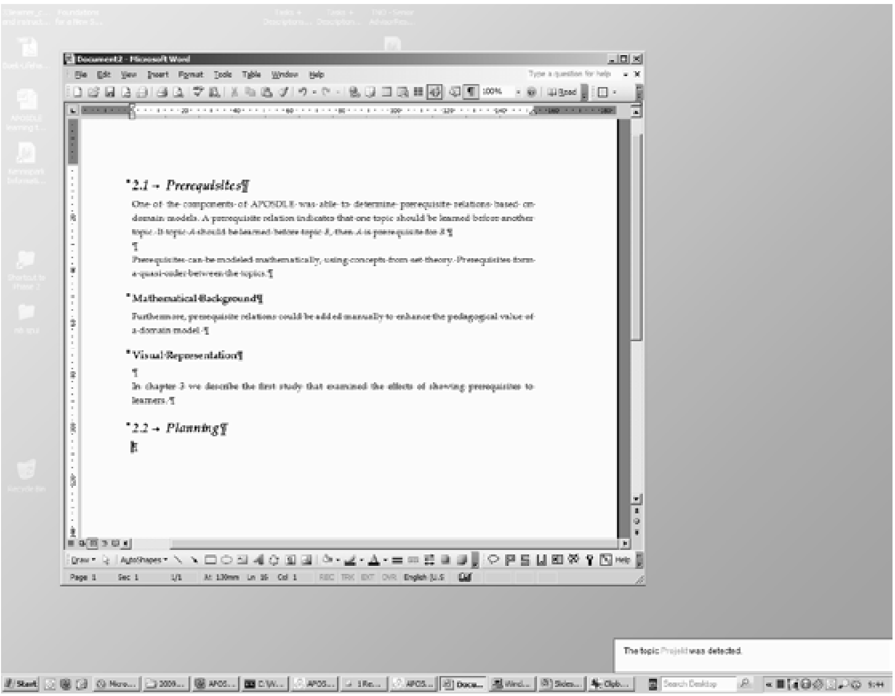
> "**Learner Support:** APOSDLE provides learners with support for *self-directed exploration and application* of knowledge. This is done *within their work environment* such that learning takes place *within the learner's current work context*. APOSDLE provides learners with guidance through the available knowledge by applying *novel learning strategies*. Content from knowledge sources are presented to learners even if the content provided has originally *not been intended for learning*."

APOSDLE was intended to be applicable in any type of industry in which people work with computers. Therefore, the tools that were developed had to be independent of the underlying working domain. Thus, the focus was not to provide a learning environment tailored to the participating application partners, but to provide a generic, domain-independent approach to computer-supported workplace learning. One of the unique selling points of APOSDLE is that the system uses available documents in the organizations' computer network and not specifically designed instructional material. The underlying rationale is that knowledge is already available in the documents in the network and, with the appropriate technology, this knowledge can be delivered to the right person, at the right time. As described above, the University of Twente was one of the twelve partners involved in the project and was responsible for the work package (WP) that addressed self-directed learning. The objectives of this WP were formulated in the project's DOW as follows:

This WP supports a Learner in her working environment. Specifically this WP

- defines **components of self-directed learning** (SDL). This concerns a) the formulation of a learning need, b) the formulation of learning goals, c) identifying resources for learning, d) selecting and executing learning strategies, and e) evaluating learning outcomes.
- designs **scaffolds to support users** to perform these components of self-directed learning. In the following these will be referred to as **APOSDLE Learning Tools**.
- designs the technological domain-independent **SDL Software Framework** which allows for the low-effort creation of learning-domain and work-environment specific APOSDLE Learning Tools.

Throughout these objectives, the term self-directed learning (SDL) is used. In Section 1.2 we have pointed out that self-regulated learning (SRL) is used as the theoretical framework of this dissertation, because it focuses more on the learning processes compared to SDL. In this section however, we use SDL and SRL interchangeably to indicate learning in which learners are responsible for their own learning process. For a detailed discussion of the differences between SDL and SRL we refer to the article by Loyens, Magda and Rikers (2008), who stated that "[…] both SDL and SRL involve active engagement and goal-directed behavior. Both entail goal setting and task analysis, implementation of the plan that was constructed, and self-evaluation of the learning process" (p. 417). The second objective of the work package mentions the APOSDLE Learning Tools. The studies described in this dissertation aimed to support the development of one such learning tool: the learning path component. The overall goal of this component was to scaffold users to plan self-directed learning activities. In order to provide intelligent planning scaffolds, the system needed some sort of understanding of the underlying learning domain and of the users' current knowledge. To accomplish this, the SDL Software Framework contained domain models describing the learning domain, task models describing the tasks, and user models describing the users' current knowledge of that domain. When the system found a discrepancy between the required knowledge for a certain task and the workers' actual knowledge, this was called a knowledge gap.



2.1 → *Prerequisites*

One of the components of APOSDLE was able to determine prerequisite relations based on domain models. A prerequisite relation indicates that one topic should be learned before another topic. If topic *A* should be learned before topic *B*, then *A* is prerequisite for *B*.

Prerequisites can be modeled mathematically, using concepts from set theory. Prerequisites form a quasi-order between the topics.

Mathematical Background

Furthermore, prerequisite relations could be added manually to enhance the pedagogical value of a domain model.

Visual Representation

In chapter 3 we describe the first study that examined the effects of showing prerequisites to learners.

2.2 → *Planning*

The topic Projekt was detected.

Figure 5. Task detection in APOSDLE.

APOSDLE was envisioned to be a software environment that would constantly run in the background on the users' computers monitoring their activities. Thus, workers could use the applications they would normally use to complete their tasks. APOSDLE would continuously monitor the running applications to determine the workers current tasks and learning needs. Figure 5 shows a screenshot of a desktop with a MS Word document. The lower right part of the screenshot shows a notification of APOSDLE that a topic was detected. Based on the detected topics and tasks, APOSDLE inferred what knowledge was required and compared this against the knowledge levels according to the user model.

When the system identified learning needs, it suggested learning opportunities to cover those learning needs; it could provide learners with learning material, but it could also suggest contacting knowledgeable colleagues. APOSDLE aimed to provide support for two different types of knowledge gaps. When the difference between the required and the actual knowledge of a user was small, the gap could be solved within one learning session. APOSDLE would search for appropriate resources and immediately suggest them to the user. This is referred to as just-in-time learning. Figure 6 shows a screenshot of a prototype of APOSDLE's user interface. The left part of the figure shows topics from the current learning domain. The right part of the screen presents the resources along with additional information about those resources. In this example, the system found one HTML page and two PDF documents. APOSDLE provided a resource viewer to view all types of documents available in the system. The resource viewer looked similar to a standard PDF viewer, but it also provided learning hints and oppertunities to find related material or to contact colleagues about the currently opened document.

When there was a large gap between the required and the actual knowledge, learners would need several sessions to process all material. In APOSDLE, the learning path component supported the planning of such larger learning sessions. A learning path is defined as a sequence of topics from the domain model that describes a path through the learning domain. During learning, learners can follow these paths as guides. Moreover, learning paths also act as a sort of bookmark; they keep track of where users are, so that learning sessions can be continued later on. With the software, learning paths could be edited, deleted, or shared with colleagues. This is where the role of the expert comes into play. Domain experts can create optimal paths and share them with novices in the organization.

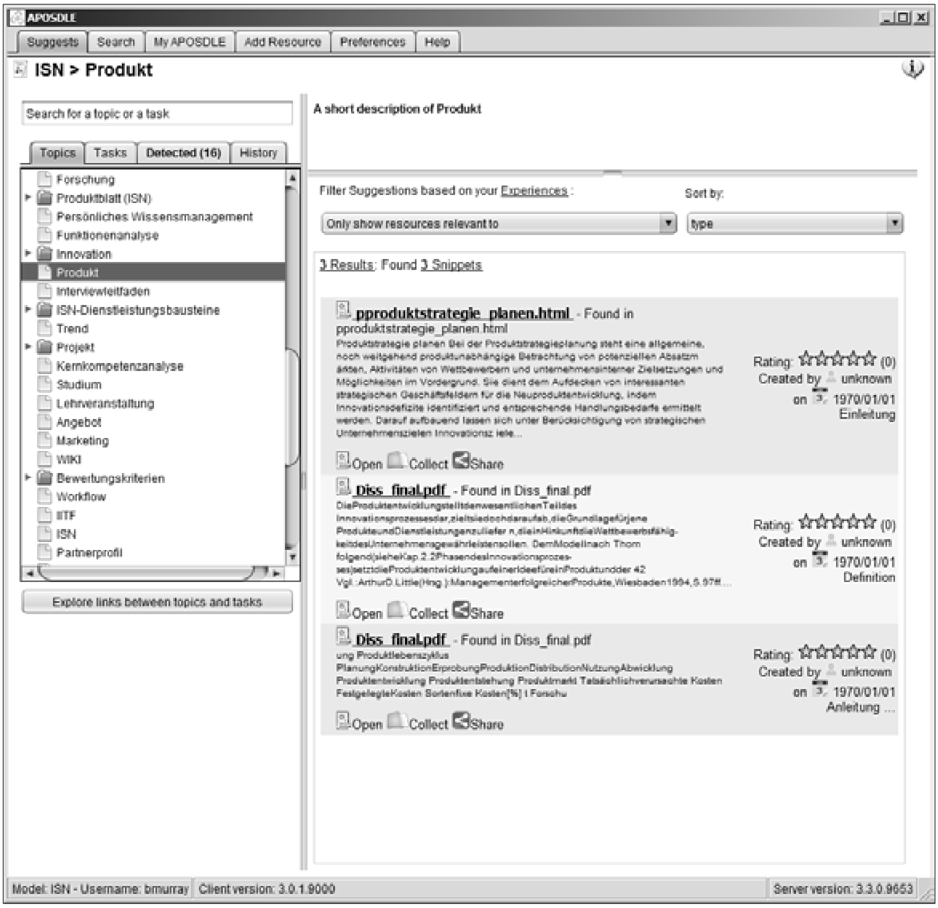


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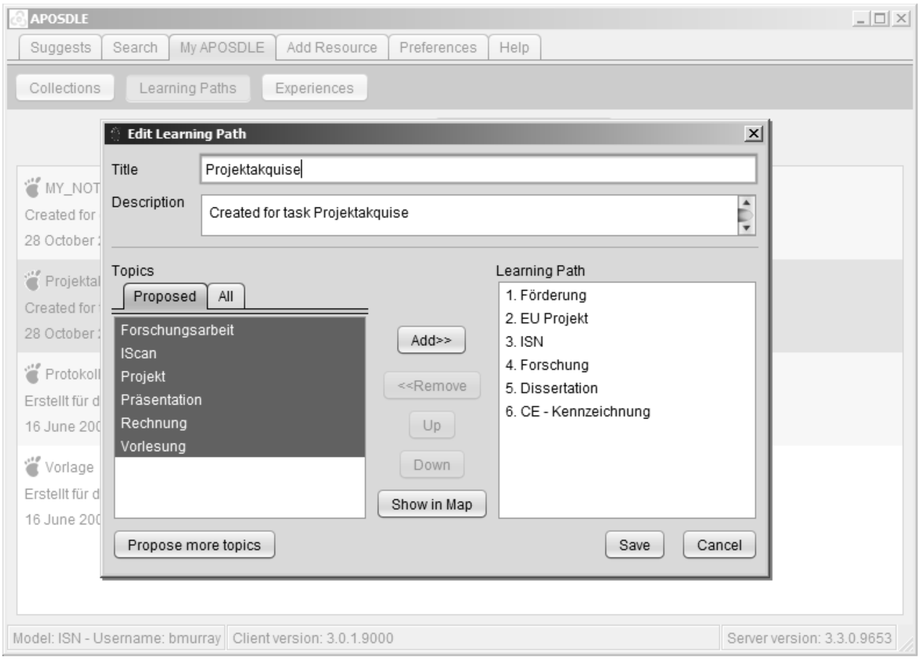
Figure 6. Prototype of APOSDLE's Graphical User Interface.

Figure 7 shows a screenshot where learning paths can be edited. The left part of the screen lists elements from the domain model that are proposed by the tool. The right part of the screen shows the current learning path. To gain insight in the relationships between the topics in the learning path, the relationship viewer shows a graphical representation of the learning path and the surrounding topics in the learning domain. Figure 8 shows a screenshot of the relationship viewer. The viewer shows tasks and topics as nodes, and the relationships as gray lines. Learning paths are visualized as bold arrows between topics. In this case, the path is a sequence of only two elements: *Agenda* and *APOSDLE*.



Title: Projektakquise

Description: Created for task Projektakquise

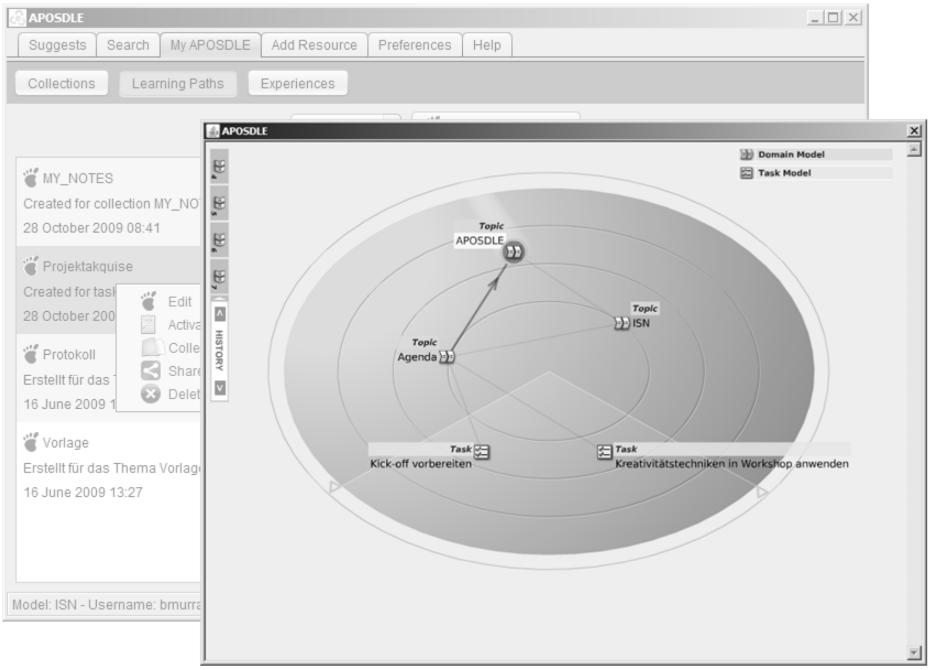
Topics (Proposed):
Forschungsarbeit
IScan
Projekt
Präsentation
Rechnung
Vorlesung

Learning Path:
1. Förderung
2. EU Projekt
3. ISN
4. Forschung
5. Dissertation
6. CE - Kennzeichnung

Model: ISN - Username: bmurray | Client version: 3.0.1.9000 | Server version: 3.3.0.9653

Figure 7. APOSDLE's Edit Form for Learning Paths.

Above, we provided a general description of the APOSDLE system. In the following sections, two specific aspects from the underlying SDL software framework are discussed in more detail. These two aspects were especially important for the decisions we made in de design process for our tools: 1) the availability of domain models and 2) the availability of prerequisite relations.



MY_NOTES
Created for collection MY_NO
28 October 2009 08:41

Projektakquise
Created for task
28 October 200

Protokoll
Erstellt für das
16 June 2009 1

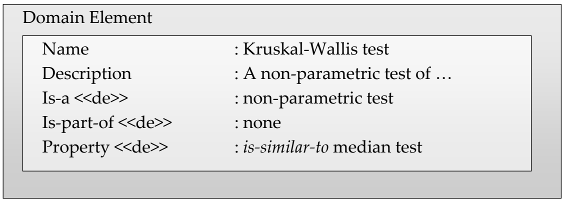
Vorlage
Erstellt für das Thema Vorlag
16 June 2009 13:27

Model: ISN - Username: bmurra

Figure 8. Visualization of Learning Path in APOSDLE's Relationship Viewer.

Domain Models

APOSDLE's SDL software framework depends on models to reason about domains, tasks, and users. By analyzing and comparing these models, the system is able to identify learning goals and to suggest appropriate learning material. In this section, we focus on the domain model. Domain models contained information about the contents and structure of learning domains. Within the project, topics in domain models were called domain elements. To give an impression of the contents of the domain models, we first describe the structure of an individual domain element and then give an example of a small domain model with three domain elements. Figure 9 shows the structure of a domain element. It shows that every domain element had a textual name and a description. Moreover, domain elements can have relationships to other domain elements. The *is-a* relationship indicated the one element was an ontological child of the other. This relationship can, for example, indicate that a median test *is-a* non-parametric test. The *is-part-of* relationship indicates that one element is part of another element. Moreover, any other relationship could be defined using the properties of domain elements. In the modelling process, knowledge engineers were free to determine the name of such user defined relationships. Because of these types of relationships, domain models had both a hierarchical structure through the *is-a* relationship and a network like structure through the *is-part-of* and user defined relationships.



Domain Element

Name : Kruskal-Wallis test
Description : A non-parametric test of …
Is-a <<de>> : non-parametric test
Is-part-of <<de>> : none
Property <<de>> : *is-similar-to* median test

Figure 9. Domain Element Structure with Example Data.

Figure 10 shows an example of a small domain model with three domain elements: *non-parametric test*, *median test*, and *Kruskall-Wallis* test. In APOSDLE, domain models were created with the use of an integrated modelling methodology with a multi-method approach. The methodology used automated text mining services such as relevant term extraction from existing documents and manual techniques such as concept listing, card sorting, and laddering. The results of such processes were informal models with relevant learning domain topics and relationships between those topics.

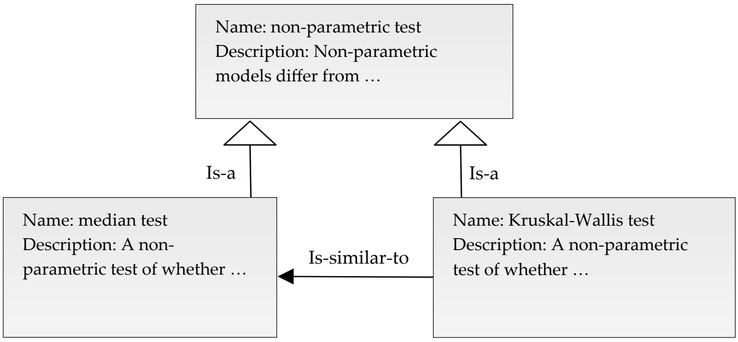


Figure 10. Small Domain Model Example.

To use these informal models in APOSDLE's SDL software framework, the models had to be transformed into Web Ontology Language (OWL) files. The models were then edited and finalized using the Protégé Ontology Editor and Knowledge Acquisition System (Gennari, et al., 2003). A complete overview of the used methodology is described in the APOSDLE deliverable D1.6, Integrated Modelling Methodology that is publicly available on the project's website (http://www.aposlde.org). According to the specification, OWL is intended to be used when the information contained in documents needs to be processed by applications, as opposed to situations where the content only needs to be presented to humans. To get an impression of the information in such OWL files, Figure 11 shows an example of the contents of a domain model file. Every class described in this example is a domain element in the APOSDLE domain model. The example shows classes from the statistical data analysis (SDA) domain.

```
    <SDAaposdle-ontology:is_reified_by  rdf:resource="#ReifExperiment"/>
</owl:Class>

<owl:Class  rdf:about="#Interaction_Effect">
    <rdfs:label  rdf:datatype="&xsd;string">Interaction Effect</rdfs:label>
    <rdfs:comment  rdf:datatype="&xsd;string">The interaction effect is the dif
    <SDAaposdle-ontology:category>Domain_model</SDAaposdle-ontology:category>
    <SDAaposdle-ontology:uri>http://aposdle.fbk.eu/AP5/index.php/Special:URIRes
    <SDAaposdle-ontology:wikipage>https://aposdle.itc.it/AP5/index.php/Interact
    <rdfs:subClassOf  rdf:resource="#Effect"/>
    <SDAaposdle-ontology:is_reified_by  rdf:resource="#ReifInteraction_Effect"/
</owl:Class>

<owl:Class  rdf:about="#Chi-Square-Distribution">
    <rdfs:label  rdf:datatype="&xsd;string">Chi-Square-Distribution</rdfs:label
    <rdfs:comment  rdf:datatype="&xsd;string">The chi-square distribution is th
    <SDAaposdle-ontology:category>Domain_model</SDAaposdle-ontology:category>
    <SDAaposdle-ontology:uri>http://aposdle.fbk.eu/AP5/index.php/Special:URIRes
    <SDAaposdle-ontology:wikipage>https://aposdle.itc.it/AP5/index.php/Chi-Squa
    <rdfs:subClassOf  rdf:resource="#Probability_Distribution"/>
    <SDAaposdle-ontology:is_reified_by  rdf:resource="#ReifChi-Square-Distribut
</owl:Class>

<owl:Class  rdf:about="#Internal_Validity">
```

Figure 11. Example of Contents of APOSDLE’s Domain Model Files.

Prerequisites

A second influential aspect of APOSDLE’s SDL software framework was the availability of prerequisite relationships between elements from the domain models. One of the goals of APOSDLE was to develop a component that could determine prerequisite relationships based on the domain models. With such a component, domain models could automatically be enriched with instructional information and the system could use that information to provide intelligent support. Furthermore, prerequisite relations could be added manually to enhance the pedagogical value of a domain model. The approach used in APOSDLE was based on the competence prerequisite structures for e-learning domains developed by Hockemeyer, Conlan, Wade, and Albert (2003). In this dissertation, we do not go into the details of the creation of the prerequisite structures, but we assume that a prerequisite structure is available in APOSDLE’s domain models.

In educational and instructional science, prerequisite relationships indicate which topics should be understood, before other topics can be understood. In a typical learning domain, the elementary topics are prerequisites for the more advanced and more complex topics. Without understanding the elementary topics, it is difficult, or even impossible, to acquire a good understanding of the advanced topics. Accordingly, prerequisite relationships describe dependencies between topics. Prerequisite relationships can be used to determine optimal paths through a learning domain. This approach is based on the classical notion of prerequisites put forward in Gagné’s learning prerequisite hierarchy (e.g., Gagné, 2005). According to his theory, optimal learning sequences must be determined based on the prerequisite relationships. Thus, learners must first address prerequisite concepts in order to learn the more advanced concepts. Most learning environments organize their learning material in such a way that the prerequisite relationships are adhered. However, we should keep in mind that there are also alternatives to this approach. An example is problem-based learning (PBL), in which learners are deliberately put in situations where the prerequisites are not adhered (Hubscher, 2001). The idea behind such approaches is that when learners themselves discover that they do not have the appropriate knowledge yet, they might be more motivated to take the initiative for solving them. In this dissertation, however, we use the approach put forward by Gagné.

Summarizing, the domain model is one of the three models that are available in APOSDLE's SDL software framework. This model contains information about the contents and structure of the learning domain. Moreover, domain models contain instructional information in the form of prerequisite relationships between domain elements. Although both the domain models and the prerequisite relationships were originally intended to support automatic reasoning of APOSDLE's software, the availability of this information clearly provides opportunities for self-directed exploration of knowledge and learning. Moreover, the prerequisite relationships allow to provide automatically generated support for self-directed exploration. In the following section, we address guidelines from literature that prescribe how such support should be developed. The last section of this chapter describes the conceptual designs of the tools used in the studies, based on the requirements from this section and guidelines from the following section.

2.3 *Technology-Enhanced Learning*

The field of technology-enhanced learning (TEL) addresses the use of technology to support learning. In TEL, technology is interpreted as a broad concept ranging from simple technologies, such as pen and paper, to advanced technologies, such as interactive whiteboards and computers. In this dissertation, we focus on one specific technology; we address the use of computer software that aims to support the learning process. With the term computer-based learning environment (CBLE), we refer to the combination of a personal computer and the accompanying educational or instructional software. Although the use of computers in education can have positive effects, such as improved accessibility and flexibility of the learning material, and individualized approaches to the learning process, it is not straightforward how to design and develop an effective CBLE. Actually, in recent years, many e-learning programs have failed to live up to their expectations (DeRouin, Fritzsche, & Salas, 2004). To prevent instructional designers from making common mistakes in the creation process, the field of TEL has developed several sets of guidelines. With such guidelines, designers do not have to reinvent or experience everything themselves, but can build on the knowledge and experience of others. Traditionally, TEL guidelines were mainly driven by the features of new technologies and by intuitive beliefs of the designers. Over the years, however, the field has matured and most guidelines are now based on research-based educational and psychological principles. Although several authors have compiled sets of guidelines aiming at specific types of learning, such as multimedia learning or inquiry learning, there is no comprehensive set of guidelines or framework for TEL yet. In their review of the TEL literature, Hannafin and Land (1997) concluded that apart from several isolated studies there was little overarching understanding on the role of technology in the whole process. This is in line with findings from Leung (2003). In his work on design issues regarding the construction of CBLEs, he identified several individual studies, but no generally accepted framework or design guidelines for the construction of such software. As a possible explanation of this absence, Leung suggested that learning is such a complex process that it might not be possible to create a comprehensive framework covering all types of learning and all types of learners.

Guidelines & Frameworks

Although there is no generally accepted overarching framework, several authors have compiled sets of guidelines for TEL. In the following section, we address several of those sets, to identify important and recurring guidelines that can be applied to the current project. DeRouin, et al. (2004) provided 16 principles for the design of e-learning programs. These principles are listed in Table 14 in the Appendix of this dissertation. In their work, they focused especially on how the aspect of learner-control should be incorporated in the design. As Table 14 shows, the authors did not only provide guidelines for the design of software, but also for organizational aspects that influence whether technology is accepted. In this section, however, we highlight several relevant guidelines that concern the design of CBLEs.

The first principle identified by DeRouin, et al. (2004) is: “Understanding learner control is half the battle” (p. 149). This means that learners must understand the purpose of using a technology, otherwise they will not use it or not use it correctly. Thus, giving learners control without explaining the rational will probably not improve learning. This is in line with findings from Bolman et al. (2007), who investigated a navigation support tool that was used in distance education. Most learners followed the advice from the tool and thought that the advice stimulated them to continue with the course. However, participants in their study also expressed that they wanted to know what the advice was based on and why it was given. Learners wanted to have insight in the reasoning mechanism of the system. The fourth guideline put forward by DeRouin et al. (2004) is: “Offer help” (p. 153). This guideline is based on the observation that learners do not always make optimal decisions in the learning process. Help, in the form of support or scaffolds, can improve the decision making process and the learning process. In their sixth guideline the authors stated that: “More Isn’t Necessarily Better” (p. 154). This guideline concerns the amount of learner control that learners have over the learning process. The authors stated that more learner control does not always lead to better learning outcomes. On the contrary, too much control can even impede the learning process, because it requires too much cognitive efforts from the learners. If learners have difficulties with regulating their learning, they are not focusing on the actual subject matter of the learning material and learning is hampered. Chalmers (2000) reviewed the literature on learning theories and instructional theories to solve common problems in the user interface of software used in the learning process. One of the suggestions was to let learners choose what to do, but give them support in the process. As an example, she described the use of colours to indicate appropriate links to learning material. The last guideline from DeRouin et al. (2004) that we highlight is their ninth guideline: "Footprints Help" (p. 155). This guideline was based on the observation that navigation in e-learning environments can be difficult and even cause disorientation of the learners in the learning material. Therefore, the guideline prescribes that software should support learners in the navigation by providing them with directions on how to find their way through the learning material. This is in line with the work from Tattersall and colleagues (2005), who used the term educational way finding to refer to self-directed navigation in an educational context. The authors said that self-directed learners can benefit from support in this way finding process. Moreover, they stated that "difficulties in the educational way finding process can lead to learners not reaching their goals, or taking unduly long to do so" (p. 110).

Park and Hannafin (1993) developed a framework that aimed specifically at multimedia learning. They composed twenty design principles based on their review of the literature on interactive multi-media. All these principles are listed in Table 16 in the Appendix of this dissertation. Modern CBLEs, such as APOSDLE, share many characteristics of interactive multimedia; the learning material in such environments is not accessed in a sequential order, but the material is segmented and learners can jump through the learning material. Thus, although the principles from Park and Hannafin were originally aimed at the design of interactive multimedia, most principles are also applicable to CBLEs.

With the requirements from the APOSDLE project in mind, some of these principles are more appropriate than others. However, two principles were especially suited for our project: principle 8 and 16. Principal 8 stated that "[l]earning improves as the amount of invested mental effort increases" (p. 73). The amount of mental effort depends on both the learner and the learning environment. Learners can perceive different levels of mental effort for the same learning environment and the same learning material. However, aspects of the learning environment can also influence the perceived amount of mental effort. As an implication of this principle, the authors suggested to embed activities in the learning environment that increase the perceived demand characteristics of both the learning material and the performed learning activities. This is in line with findings from Hannafin and Land (1997), who reviewed the literature and identified several articles that offered guidelines and heuristics for the design of TEL environments. One of their findings was that "[u]nderstanding is best supported when cognitive processes are augmented, not supplanted, by technology" (p. 187).

In principle 16, Park and Hannafin (1993) stated that "[v]isual representations of lesson content and structure improve the learner's awareness of both the conceptual relationships and procedural requirements of a learning system" (p. 78). Graphical representations provide a different view on the learning material. Learners can use such views to understand the underlying structure of the learning domain. As an implication of this principle, the authors suggested to visualize interrelationships among concepts, and to use graphical overviews to indicate the current location of the learner relative to other learning material. The authors also recognize that there are many design decisions that must be tackled when a graphical overview is used in a learning environment. This is in line with findings from Clark and Mayer (2008), who recommended to use course maps, especially when learning material is lengthy and learners are novices. Although the authors provide some guidelines on how to apply learner control in CBLEs, they also notice that the current findings on research on graphical overview are complex to interpret and that more research is needed in the area of navigational elements, such as graphical overviews. The study described in Chapter 3 of this dissertation addresses the enhancement of a graphical overview, and in that chapter we examine the literature on the effects of graphical overviews on learning in more detail.

Jacobsen and Archodidou (2000) developed a hypermedia tool that aimed to support learners in the construction of deep understanding of challenging knowledge. To reach that goal, they created and applied a framework describing design and pedagogical principles for hypermedia learning tools. Their framework was built around the concepts of design elements and corresponding learning activities. An overview of all four design elements (with sub elements) is shown in Table 15 in the Appendix. Their first design element concerns representational affordances of technology. This element emphasizes that modern technologies offer representational possibilities that traditional educational material did not have. For example, with today's computers it is possible to display learning domains with graphical overviews and to adapt such overviews to characteristics of the learners dynamically. To realize the full potential of CBLEs in education, the authors suggested that designers should make use of such affordances in the design of learning environments.

The second design element identified by Jacobsen and Archodidou (2000) focused on the context in which the learning material is presented, such as the used cases and problems. Because we do not have influence on the context of the software that is developed during this research, this element is not applicable for our project. The third and fourth design elements, however, are of interest for our tools. The third design element is based on the observation the novices typically focus on surface features and that they fail to understand the conceptual deep structure. Jacobsen and Archodidou (2000) emphasized that abstract domain elements and structural aspects of the learning domain should be made explicit, so that novice learners can more easily see the abstract concepts that the material is dealing with. The authors also recommend to graphically visualize concepts and structures. This can be done with domain independent graphical overviews, but also with domain specific conceptual visualizations, such as runnable models or simulations. The fourth design element concerns the linking of learning material. This design element is based on the observation that novices have difficulties identifying the crucial aspects of learning material, especially if the learning material was not specifically designed for educational purposes. The authors suggest to have a sort of abstraction layer that identifies the important aspects. In this way, learners can browse to documents that address the same topics, although this is not clearly visible from the surface features of the material.

The principles, guidelines, and frameworks described in the current section, addressed various types of learning and learning environments. However, so far they did not address the support of specific tasks, such as planning the learning process. We now focus on the specific aspects of the planning process and how it can be integrated in a CBLE. To support planning, we identified it as a typical problem-solving task. Based on the classification put forward by Jonassen (2005), planning can be identified as a conceptual problem solving activity in which the problem is ill-defined. In the planning process, there are many competing solutions to achieve the learning goal and there are no clear guidelines to evaluate the different alternative plans. To support such problem solving, Jonassen (2005) prescribed to graphically visualize the problem space. In this situation, the problem space is the learning domain. We have seen that the use of graphical overviews that visualize the structure of the learning domain is a technique that is typically used in educational settings. During the research described in this dissertation, we developed and researched several versions of a software tool that explicitly visualized the learning domain to support the planning process in an electronic learning environment.

In this section, we have addressed several sets of guidelines and frameworks that all aimed to guide the development of TEL. One observation was that the sets of guidelines address different types of learning and learning environments. Accordingly, the sets provided a wide variety of guidelines. During the review of these lists, it became clear that some aspects were applicable to our project, and some aspects do not fit in the APOSDLE ideology or are not applicable at all. The guidelines strengthened the idea that planning is an activity that potentially is beneficial for the learning process and that planning could be supported with graphical visualizations.

2.4 Conceptual Designs

Three studies were performed during the course of this research project. All studies aimed to guide the development of a planning component for the APOSDLE system. Several design guidelines appeared to be applicable to the design of such a planning component. In the following sections, we describe the conceptual designs of the tools used in our studies. It might appear that the designs of the tools were all constructed independently, however, this is not the case. We used an ADDIE approach with three iterations, in which observations from the first tool were used in the analysis and design of the second tool, and lessons from the second tool were used for the third tool. Although the tools used in the different experiments look similar, there are some important differences between them. In this section, the tree tools are described in detail.

Software for First Experiment

The first experiment focused on the visualization of the domain models and on the effects of the visualization of prerequisites. The tool contained learning material to support the tasks of learners. The learning material was accessible through a graphical overview that visualized the network-like structure of the domain. The learning material was segmented in such a way that every topic was explained in one resource. To understand a certain topic, learners were expected to browse through several topics, from prerequisites to the goal topic. In this tool, planning was not implemented as an explicit task. Learners were expected to browse through the learning domain according to the provided visualization of prerequisites. Figure 12 shows the conceptual design of the tool used in the first study. For every topic in the domain model, the learning environment contained several resources. When an element from the graphical overview was selected, the direct prerequisite relationships were displayed in the graphical overview. In Figure 12 this is represented as the big arrow from T*opic2* to T*opic1*. Furthermore, a list with available learning material about the subject was displayed in the resources list. When learners would select a document from the resources list, this was shown in the right part of the screen, instead of the graphical overview.

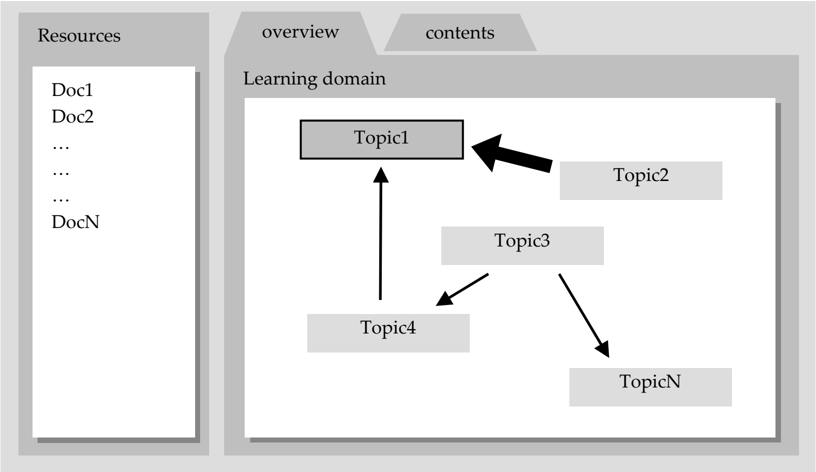


Figure 12. Conceptual Design of the Graphical Overview with on the left the list of resources for the currently selected topic in the right part of the screen.

Thus, when learners had selected a topic in the graphical overview, the corresponding resources were shown in the left part of the screen. When users selected a resource, the contents of the resources were shown on the main part of the screen. This is shown in Figure 13.

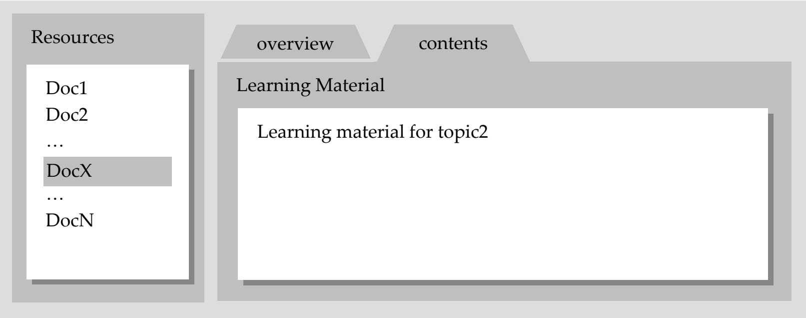


Figure 13. Conceptual design of displaying learning material.

Software for Second and Third Experiment

Whereas the planning was performed implicitly in the first study, planning was explicitly supported in the second and third study. The conceptual design of these tools is shown in Figure 14. The left part of the figure shows the current learning goal and the learning plan to reach that goal. In the tools, a learning plan was defined as a sequence of topics from the learning domain. The goal of a learning plan is to master one or more learning goals. Learning goals are also concepts from the learning domain. To change the learning plan, elements could be moved around the list. Elements could also be removed by selecting them and by pressing delete, or by selecting them and clicking the “remove” button. To add elements to the learning plan, elements could be dragged and dropped into the right position in the list, or users could right click on elements and select “add to plan” from the context menu. In this case, the topic was added to the end of the current learning plan.

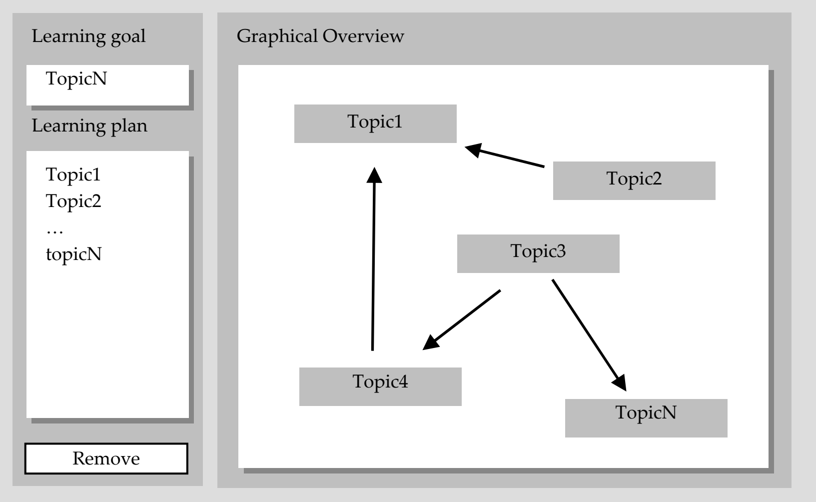


Figure 14. Conceptual Design of the Planning Component with on the left the Learning Plan list and on the right the graphical overview of the learning domain.

This way of creating a plan was used in both the software for the second and the third study. The representation of the actual learning material was different for the second and third study. In the second study, the graphical overview contained definitions of the topics. This information could be read by hovering the element. In the third study, however, the plan was used to order the available learning material. Once the plan was created, the learning material could be traversed according to the plan. The conceptual design of this traversal is shown in Figure 15. The left part of the figure shows the learning goal and the learning plan. The right part of the screen now shows the actual learning material corresponding to the topic that is currently selected in the learning plan. The learning plan can be traversed with a previous (<<) and a next (>>) button.

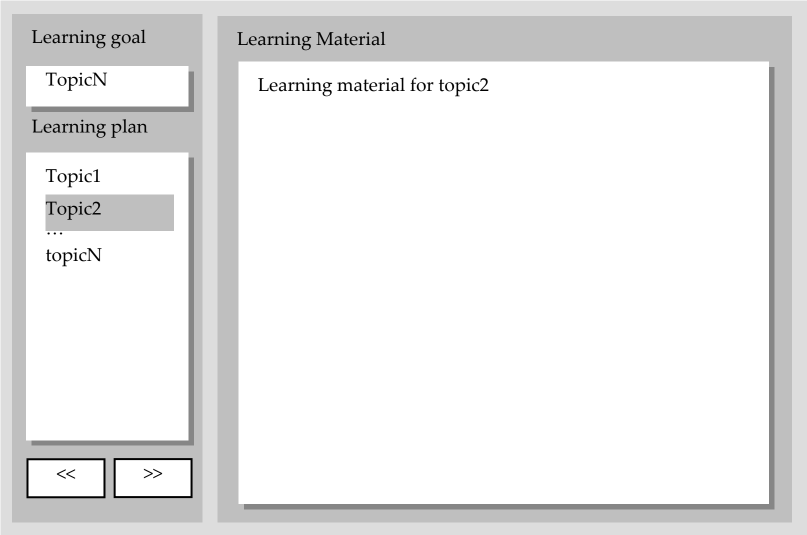


Figure 15. Conceptual Design of the tool with on the left the Learning Plan list and on the right the learning material for the currently selected topic.

Prerequisites

A prerequisite relation from topic *A* to topic *B* indicated that *A* had to precede *B* in the learning process. Prerequisites were only displayed as the user selected the associated topics. We used this visualization because there were many prerequisite relationships and showing them all at once resulted in complicated dense graphs, in which all elements had many relationships. Some initial trials with such visualizations pointed out that graphical overviews with all prerequisite relationships presented were too complex to interpret and were not usable for the learning process.

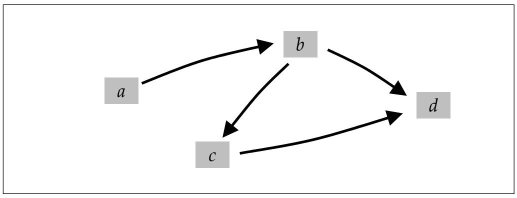


Figure 16. Prerequisite relations.

Figure 16 shows a schematic display of prerequisites. In the figure, we see that element *a* must be learned before *b*, *b* before *c*, *b* before *d*, and *c* before *d*. Planning the learning process for element *c* would result in the (ordered) sequence (*a*, *b*, *c*). The figure demonstrates that the position of the elements do not determine the semantics of the connection. The arrowhead indicates how the relation must be interpreted. In Chapter 3 we describe the first study that examined the effects of showing prerequisites to learners. In Chapter 4 and 5, the visualizations are used to support the planning process. To implement domain models, prerequisite relationships, and learning plans in our software, we described these concepts in a more formal way. The concepts can be modelled using set theory. Elements from the domain model, the domain elements, form a set:

$$D = \{t_1, t_2, ..., t_n\} \qquad \text{Learning Domain Topics} \qquad \text{I}$$

The prerequisite relation is a binary relation on the set of learning domain topics. The binary relation *is-prerequisite-of* is defined by:

$$P = \{ (t_i, t_j), (t_k, t_l), \dots \} \quad t_n \in D \qquad \text{Prerequisite relationship} \qquad \text{II}$$

There are some more restrictions for this relationship. First, a topic cannot be a prerequisite for itself. Accordingly, the prerequisite relationship is irreflexive. Second, if element *a* is prerequisite for *b*, and *b* is prerequisite for *c*, than *a* is also (indirectly) prerequisite for *c*. Thus, the prerequisite relationship is transitive. Third, if a topic *a* is prerequisite for topic *b*, than topic *b* cannot be a prerequisite for topic *a.* Thus, the prerequisite relationship is asymmetric.

$$(t_a, t_a) \notin P \qquad \text{(reflexivity)} \qquad \text{III}$$

$$(t_a, t_b) \wedge (t_b, t_c) \in P \Rightarrow (t_a, t_c) \in P \qquad \text{(transitivity)} \qquad \text{IV}$$

$$(t_a, t_b) \in P \Rightarrow \neg (t_b, t_a) \in P \qquad \text{(asymmetry)} \qquad \text{V}$$

These properties together assure that the prerequisite relationship forms a strict partial order. It is partial, because the relation does not have to hold for all elements in a domain; some topics in a learning domain do not have a prerequisite relation. Since, the prerequisite relationship forms a strict partial order, set theory proves that the relation can be mapped to a directed graph with no cycles, a directed acyclic graph. This is important, because this ensures that there are no infinite loops when prerequisite relationships are used to sequence learning topics. With this formal representation of the prerequisites, we can also define correct learning plans. A learning plan *LP* is a sequence of topics from learning domain *D*. It is possible to check whether a learning plan adheres the prerequisite relations.

$$LP = \left(t_a, t_b, \ldots, t_n\right) \quad t_i \in D \qquad \text{Learning plan} \qquad \text{VI}$$

In a correct learning plan, the learning goal must be the last element in the plan. Furthermore, the learning plan must contain all (direct and indirect) prerequisite elements of the learning goal. Learning plans must only contain relevant topics. Accordingly, learning plans must not contain topics that are not prerequisites of the learning goal. Thus, to determine whether a learning plan is correct for a given set of topics *D*, prerequisites *P*, and a learning goal t_{goal}, the following three predicates must all be true.

$$L(LP) = t_{goal} \qquad \text{VII}$$

$$\forall p \, \forall t \, \left(P\left(p,t\right) \Rightarrow B\left(p,t\right)\right) \quad p \in LP, t \in D \qquad \text{VIII}$$

$$\forall p \, \exists\left(t_a, t_b\right)\left(t_a = p \wedge t_b = t_{goal}\right) \quad p \in LP, (t_a, t_b) \in P \qquad \text{IX}$$

Note. P(a,b) means that *a* is a prerequisite for *b*. *B(a,b)* means *a* precedes *b* in the sequence *LP*. *L(x)* denotes the last element of a sequence.

This formalization shows that there is not always one correct learning plan. For some given domain models and learning goals, there might be several correct learning plans. Although all correct plans contain the same elements, the order of the elements can be different as long as three predicates described above are true.

In this chapter, we have described the overarching project in which this work was performed. Furthermore, we have described guidelines from TEL and SRL literature for the development of learning environments. These guidelines and the requirements from the project inspired the direction of the research that is described in this dissertation. The last section from the current chapter described the conceptual designs for the tools used in this dissertation. In the following chapters, Chapter 3, 4, and 5, we describe the three studies that were performed with these tools. In those chapters, we address the corresponding literature in more detail.

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Chapter 3

Instructional Cues in Graphical Overviews: The Effects of Visualizing Prerequisite Relations [*]

Abstract
Graphical overviews can help learners to grasp the structure of a learning domain. The design of such overviews influences how learners interact with that domain. In this study, a graphical overview was enhanced with an instructional aid: the visualization of prerequisites. The dependent variables were navigational behaviour, task performance, and learning outcomes. Forty-two participants worked on a set of statistical problems while supported by a software tool. This tool contained a graphical overview of the domain of statistics with resources for every topic. In the experimental condition, prerequisite relationships were visualized in the graphical overview. Navigational behaviour of the participants was recorded in log files, task performance was based on the quality of the task outcomes, and learning was measured with a multiple choice knowledge test. Significant effects were found for navigational behaviour: the visualization of prerequisite relations in graphical overviews guided browsing behaviour for well-structured tasks, but not for ill-structured tasks. The visualization of prerequisites did not influence task performance or learning outcomes.

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[*] This chapter is based on: Bonestroo, W.J. & de Jong, T. (2010). Instructional cues in graphical overviews: The effects of visualizing prerequisite relations. Manuscript in preparation for publication

3.1 Introduction

Knowledge in human long term memory is hypothesized to be organized in cognitive structures that contain the encoded knowledge and beliefs about the world around us. A subject is said to be understood if the knowledge chunks in the cognitive structure are well-connected to related chunks and have production rules that operate on them (Anderson, et al., 2004; Bransford, 2000). Learning is the process of changing one's cognitive structures. Piaget speaks of assimilation of new knowledge into the existing knowledge structures and accommodation of the existing knowledge structures to make place for new information (McVee, Dunsmore, & Gavelek, 2005).

A typical example of a domain that requires well-connected understanding is mathematics (Tall, 1991). In this study we focused on a specific area of mathematics: statistical data analysis. Statistical data analysis is widely taught at universities and is generally considered to be a difficult topic. An important issue in statistics education is that students often do not understand the relationships between important concepts. Doorn and O'Brien (2007, p. 2) wrote that students "in introductory statistics courses lack an understanding of the relationship among important concepts in statistics […] They see statistics as a series of disconnected topics." Furthermore, Schau and Mattern (1997) stated that "connected understanding is a prerequisite for effective and efficient statistical reasoning and problem solving" (p. 1). Orton suggested that "learning mathematics consists very largely of building the understanding of new concepts onto and into previously understood concepts" (2004, p. 20). As a consequence, certain topics must be understood before others can be understood. In this case these topics have a prerequisite relationship. Prerequisites can provide information about how to traverse a complex learning domain (Hubscher, 2001). Several recent educational technologies incorporate the concept of prerequisite relations (e.g. Hockemeyer, Conlan, Wade, & Albert, 2003; Tseng, Sue, Su, Weng, & Tsai, 2007).

Graphical Overviews

On the basis of Piaget's ideas of knowledge structures and learning, Ausubel developed the concept of advance organizers. An advance organizer should "provide ideational scaffolding for the stable incorporation and retention of more detailed and differentiated material that follows in the learning passage" (Ausubel, Novak, & Hanesian, 1978, p. 172). In line with these ideas, a number of types of graphical representation that represent the structure of a learning domain have emerged, including semantic networks (Quillian, 1967), graphic organisers (Winn, 1991), concept maps (Novak & Cañas, 2006), knowledge maps (O'Donnell, Dansereau, & Hall, 2002), and topic maps (Dicheva & Dichev, 2006). These representations have in common that they use labelled nodes to represent concepts and links between the nodes to represent relationships between the concepts. Graphical overviews represent a high-level overview of the knowledge in a domain, allowing users to explore the concepts and the relationships between them without being exposed to the detailed learning material. Furthermore, they can visually guide users through a domain and can act as a scaffold for the creation of cognitive structures (Ausubel, et al., 1978). Figure 17 shows an example of a graphical overview that visualizes the interconnected character of a part of the learning domain used in this study. The vertices represent the concepts in the domain and the labelled edges describe the relationships between the concepts.

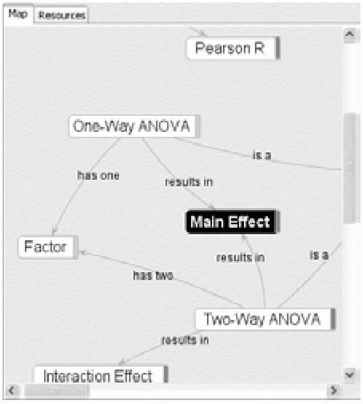


Figure 17. Example of a graphical overview in the support tool.

Because graphical overviews contain only the structure of a domain, they are not useful for studying topics in detail. One way to apply graphical overviews in education is to associate the topics in the overview with more detailed resources, such as textbook chapters, assignments, links to websites, movies, presentations, text documents, etc., (Dicheva & Dichev, 2006; Tergan, 2005). Graphical overviews come in a variety of styles and technological advances have extended their possibilities. For example, overviews can rearrange themselves according to the user's actions, hide topics that are irrelevant for the learner, or draw attention to important topics. Vekiri (2002) showed that cues in overviews can help to guide learners to important parts. Furthermore, the structuring of the topics in the graphical overview influences how people navigate through the overview (de Jong & van der Hulst, 2002). According to O'Donnell, Dansereau and Hall (2002), learners easily recognize elements that are similar (similarity), grouped closely together (proximity) and show good continuation (continuity). They conclude that graphical overviews that are designed according to these Gestalt principles are most effective for learning.

Effects of Graphical Overviews on Learning

As learning is the assimilation of new knowledge into existing cognitive structures and the accommodation of the existing structures to make place for new information, one would expect that representations that mimic the optimal cognitive structures would facilitate learning and understanding. There is considerable research showing that, overall, the use of graphical overviews in education has beneficial effects on learning and navigation. In their meta-analysis of fifty-five studies on concept and knowledge maps, Nesbit and Adesope (2006) found that creating, modifying, and reading maps all had positive effects on learning. More specifically, they found that studying maps was more effective than studying texts or outlines. McDonald and Stevenson (1998b) found that maps improved text comprehension and were better than content lists. All seven studies reviewed by Chen and Rada (1996) supported the hypothesis that graphical maps that visualize the organization of a hypertext have significant positive impact on the usefulness of a hypertext system.

However, not all studies on graphical overviews show only positive effects. Doorn and O'Brien (2007) found just slight evidence that concept mapping was effective for learning statistics. Jonassen (1993) found that factual recall did not improve when knowledge maps were used, as compared to the use of lists. He concluded that "merely showing learners structural relationships, without a purpose for doing so, is probably not sufficient to result in meaningful encoding of that information. When structural knowledge outcomes are required, learners apparently do attend to the structural information and encode it into memory". De Jong and van der Hulst (2002) studied the effects of graphical overviews on navigation and learning. They found that a structured graphical overview and an unstructured graphical overview with hints led to traversing the material in a more "domain related sequence", whereas the participants with unstructured overviews jumped through the nodes. Although a more domain related browsing sequence is likely to result in better learning results, their data did not support the hypothesis that a structured exploration pattern did result in better relational knowledge.

To explain these mixed findings, we need a more refined model that describes the relationship between graphical overviews and learning. There are a number of factors that influence the effects of graphical overviews.

Prior Domain Knowledge

The learner's prior knowledge seems to be an important factor in determining the effectiveness of knowledge maps. Hofman and Oostendorp (1999) found that a structural overview had a negative influence on the comprehension of learners with low prior knowledge. Potelle and Rouet (2003) found that network maps were not as helpful to readers with low prior knowledge as hierarchical maps. They concluded that the optimal representational form depends on the prior knowledge of learners. Scheiter and Gerjets (2007) claimed that enhanced learner control can lead to disorientation, distraction, and cognitive overload, especially for learners with low prior knowledge or with low metacognitive skills. Apparently, learners with low and high prior knowledge have different characteristics and different requirements for information presentation. High prior knowledge learners can rely on their existing cognitive structures to interpret the new information and develop a comprehensive structure, whereas low prior knowledge learners cannot. Therefore, low prior knowledge students need guidance, such as visual aids, to avoid disorientation.

Learner Characteristics

Scott and Schwartz (2007) studied the role of metacognition in the use of navigational maps. They found that learners' metacognitive skills mediated the usefulness of complex navigational maps. Learners with high metacognitive skills outperformed the learners with low metacognitive skills with the advanced maps. However, learners with low metacognitive skills outperformed learners with high metacognitive skills when using the basic maps. Scott and Schwartz explain their results using the Expertise Reversal Effect (Kalyuga, Ayres, Chandler, & Sweller, 2003). This effect implies that the effectiveness of some instructional techniques depends on the prior knowledge and metacognitive skills of the learner. Scheiter and Gerjets (2007) summarized findings from several studies to claim that hypermedia is beneficial for learners with "positive cognitive styles and attitudes towards learning" (p. 293) and that high levels of learner control should only be used for learners with high metacognitive skills. Chen and Rada (1996) compared the effects of active and passive cognitive styles on the effectiveness and efficiency of hypertext systems. They found that neither effectiveness nor efficiency was significantly influenced by the cognitive style of the learners. However, spatial ability did positively influence efficiency. Overall, it seems that a more complex visualization is more suitable for learners with high metacognitive skills, whereas a more simple visualization is more suitable for learners with low metacognitive skills.

Learning Goals

In order to be effective, a cognitive tool should have characteristics that match the characteristics of the task (McDonald & Stevenson, 1998a). For example, a graphical overview might have very different effectiveness for finding factual information than for understanding the structure of a learning domain. Insofar as graphical overviews visualize the structural organization of the subject matter, they are assumed to facilitate the construction of well-connected cognitive structures. In order to create well-connected cognitive structures, learners should get involved with the learning material. Maps can be used as scaffolds for such active processing strategies (O'Donnell, et al., 2002). Lim, Lee and Grabowski (2008) found that overviews created by learners were more effective than maps created by experts. An explanation of their findings is that learners might not be as actively involved in the learning process when they are provided with a map. Because the map already presents the structure of the learning domain, learners might not structure the knowledge themselves, and thus not get actively involved in the learning material.

Task Characteristics

Learners can use cognitive tools to support a variety of tasks. Chen and Rada (1996) differentiated between open tasks and closed tasks. Similarly, Jonassen (2000) referred to well-structured and ill-structured tasks. Well-structured or closed tasks present all elements of the problem to the learner, require the application of a finite number of rules and principles, and have a knowable, comprehensible solution. Ill-structured or open tasks, on the other hand, have elements that are unknown, have multiple solution paths, and have multiple criteria for evaluating solutions. There is uncertainty about which concepts, rules or principles are necessary for the solution and how they are organized. Chen and Rada found that users could perform open tasks more effectively and efficiently when using hypertext systems. They concluded that "open tasks can be so cognitive resources demanding that neither indices nor tables of contents have sufficient power to guide users browsing through hypertext or to augment users' cognitive ability to integrate information from multiple resources. On the other hand, graphical maps were appropriate tools for open tasks, so that a certain amount of complexity was reduced by the graphical maps." (p. 143)

Research Question

This study was performed in the context of the APOSDLE project. The project aims to develop software that supports knowledge workers in learning while they are working. The project uses domain models to provide learners with appropriate resources. The visualization of domain models can lead to immense graphical overviews. The goal of this study was to enhance graphical overviews so that they are better suited to guide learners through the overview and to help learners to construct well-connected knowledge. Prerequisite relations were added to graphical overviews as an instructional cue. The present study undertakes to examine the effects of visualizing prerequisite relations in a graphical overview on browsing behaviour, task performance, and learning outcomes. Of the identified factors that influence the effects of graphical overviews, the task type and learning goal types are included in this study. Two task types were identified: tasks with well-structured and ill-structured problems. Furthermore, two knowledge types were targeted in the post test: factual knowledge and conceptual knowledge.

Based on the research presented above, the expectation was that browsing behaviour would be positively affected by the visualization of prerequisites. Participants with the prerequisite relations were expected to have more domain-related browsing behaviour. They were expected to open more relevant and fewer irrelevant topics. Furthermore, because of the dependencies between topics in the statistical domain, it was expected that domain-related browsing behaviour would lead to better conceptual knowledge. Participants with the visualization of prerequisites were expected to produce better quality responses on assigned problems, due to a better understanding of the problems. Overall, presenting prerequisite relations was expected to have more beneficial effects for ill-structured problems than for well-structured problems, as ill-structured problems have higher cognitive demands.

3.2 Method

Design

This study used a between-subjects experimental design. The independent variable was the availability of the prerequisite visualization in the graphical overview. There were two conditions: the prerequisite condition and the control condition. Each participant was randomly assigned to one of these conditions. Dependent variables were browsing behaviour, the quality of task outcomes, and the knowledge of the participants. The log files of the tool were analysed to determine browsing behaviour in the supportive tool. The number of topics that was opened by the user was counted. For every assignment, each topic was classified as the main topic, a prerequisite topic, or an irrelevant topic.

Participants worked on well-structured and ill-structured tasks. The quality of the tasks was assessed by assigning points to the individual assignments, according to an answer model. The quality of the tasks was defined as the total score across all twelve assignments. Knowledge was measured with a multiple choice test with 21 questions. The test was administered at the end of the sessions. The test contained both factual and conceptual questions.

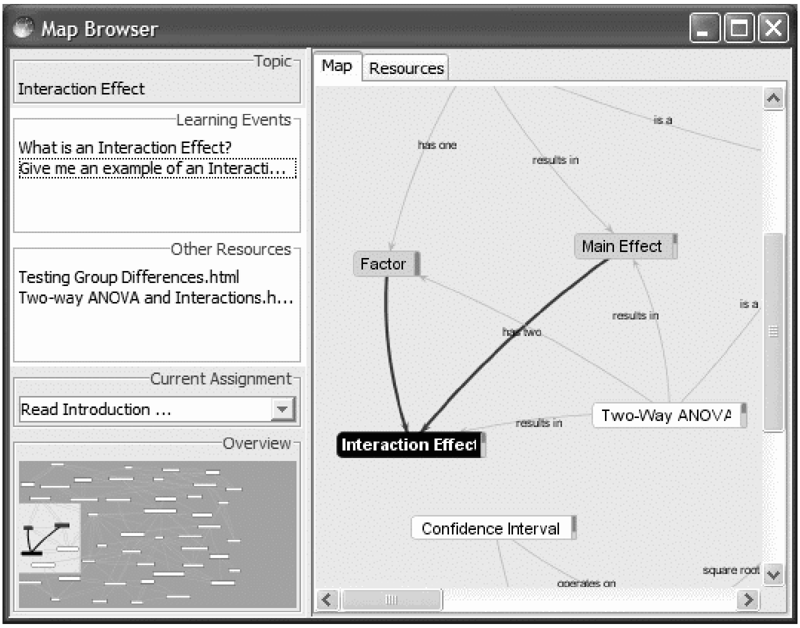
Participants

Participants were 42 students in Social Sciences (11 males and 31 females), who had completed the courses Introductory Statistics and Data Analysis 1 and who were enrolled in Data Analysis 2. Their average age was 21 years (*SD* 2.4). The introductory statistics course addressed basic statistics and probability, such as stem and leaf diagrams, histograms, central tendency measures, distributions, correlation and regression. The data analysis courses addressed t-test, confidence intervals, chi-square tests for independence, analysis of variance and regression analysis.

Material

Participants worked on a desktop computer with the supportive tool, SPSS and Word installed. All tests and tasks were carried out on that computer. Participants were provided with an SPSS file containing data. The tasks consisted of nine smaller well-structured problems and three larger ill-structured problems. All tasks could be accomplished by applying the appropriate data analysis technique. Participants could use SPSS to accomplish the tasks and Word to report their answers. They were not allowed to use any help other than the supportive tool.

The graphical overview in the supportive tool contained 48 topics from the domain of data analysis. Some examples of the topics were: normal distribution, ANOVA, samples, and t-test. For every topic, the knowledge level that was reported by the participant was shown in the graphical overview as a small bar next to the topic. Furthermore, the graphical overview contained relations between topics. This graphical overview was iteratively constructed by asking experts to provide feedback on the developed domain model. The elements were ordered according to the Gestalt principles proposed by O'Donnell and Dansereau (2002). Some relations were removed to increase the readability of the graphical overview. The graphical overview contained the concepts, the relationships and the prerequisite relations.



Topic
Interaction Effect

Learning Events
What is an Interaction Effect?
Give me an example of an Interacti...

Other Resources
Testing Group Differences.html
Two-way ANOVA and Interactions.h...

Current Assignment
Read Introduction ...

Figure 18. Prerequisites in the graphical overview.

Figure 18 shows the user interface of the supportive tool. The dark arrows in the figure represent prerequisite relations and mean that the topics of 'factor' and 'main effect' are used in the explanation of 'interaction effect'. A prerequisite relation between two topics occurred when the explanation of one topic contained another topic from the graphical overview. The supportive tool contained resources from introductory statistics textbooks, websites and pdf-documents. The lists at the left of the screen show the resources available for the selected topic. A simple document viewer was used to open the resources in the tool.

In the prerequisite condition, the tool visualized prerequisites when users selected topics. The visualization is demonstrated in Figure 19. In the first picture, no topic is selected. In the second picture, ‘variance’ is selected and the tool indicates that ‘mean’ is used in the explanation of ‘variance’. In the third picture ‘ANOVA’ is selected and the tool indicates that ‘variance’ is used in the explanation of ‘ANOVA’.

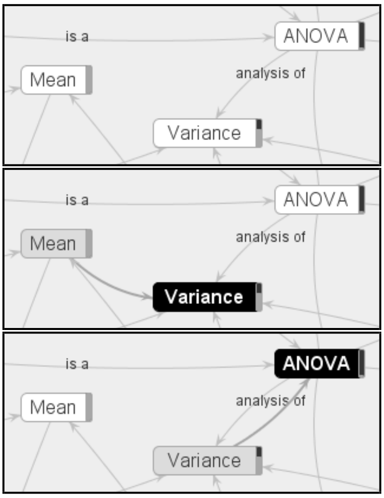


Figure 19. Visualization of Prerequisite Relations in the Graphical Overview.

The assignments could be solved by applying the right data analysis techniques. For the well-structured assignments, the right analysis techniques were given in the question. For the ill-structured assignments, participants were free to select how they approached the assignment. Once they had selected and applied an analysis technique, they were to interpret the results provided by the software and write down their conclusions. They could access the supportive tool at any point during the session. When they selected a topic in the tool, they were provided with several short documents explaining the topic.

Measurements

At the start of the session, participants completed a self-report knowledge questionnaire in which they were asked to indicate their own prior knowledge. They were asked to indicate on a 5-point scale how well they had mastered each of the topics in the graphical overview. A self-report questionnaire was used for this pre-test because a measure was needed of participants’ prior knowledge of all 48 topics in the graphical overview, and a knowledge test would have taken too much time at the start of the experiment.

After the self-report knowledge test, participants filled in a questionnaire that addressed general information such as age and gender, marks for related courses, and mapping prior knowledge. With regard to mapping prior knowledge, participants were asked to indicate how well they knew techniques such as concept mapping and mind mapping, whether they had created maps themselves, and whether they had used maps created by others. This gave two scores, one for mapping experience and one for mapping knowledge.

The post-test measuring factual and conceptual knowledge was a multiple choice knowledge test consisting of 21 items administered at the end of the session. The test contained 12 factual knowledge questions and 9 conceptual knowledge questions. Each question had four alternative answers of which only one was correct. A factual question could be answered with knowledge about a single topic. The conceptual questions addressed several topics at the same time.

Procedure

Participants were tested in the computer laboratory in groups of approximately ten people. The study session took two hours to complete. In the first 10 minutes, participants started the tools and read an introductory text. Then participants got 15 minutes to fill in the prior knowledge self-report questionnaire and to read the instructions. Results from this questionnaire were directly applied in the software environment to visualize the knowledge level of the user in the graphical overview. Participants were then provided with a description of a fictitious study with accompanying data. They were asked to analyse the data using SPSS software and to respond to the assignments using Word. They worked for 75 minutes on the tasks. Once they had finished their assignments or when the time limit was reached, the participants had 20 minutes to complete the multiple choice knowledge test.

3.3 *Results*

Both parametric and non-parametric tests were used to test our hypotheses. When a data distribution violated the parametric assumptions, a Mann-Whitney U test was used. Otherwise a t-test was used. The effect sizes were calculated according to the techniques proposed by Rosenthal (1991).

First the two groups were compared to check for a priori structural differences. Their marks on examinations for statistics, prior experience with concept maps, and scores on the pre-test were compared. There were no differences between the groups based on their marks for introductory statistics and data analysis, $U = 192$, $p > .05$. The scores on the self-report questionnaires revealed no differences, $U = 181.5$, $p > .05$. There were also no differences in prior experience with concept mapping, $U = 210.5$, $p > .05$, and in reported knowledge on mapping, $U = 202$, $p > .05$. In conclusion, there were no relevant initial differences between the two groups.

Navigation

There were no differences between the amount of time that participants used the supportive tool, the time they spent using the graphical overview, or the time they spent with the resources, ($U = 198$, $U = 199$, $U = 203$, respectively). Table 1 shows the average number of seconds that participants used the tool.

Table 1

Average times and mean ranks for times working with different parts of the tools.

	With Prerequisites		Without Prerequisites	
	M (*SD*)	Mean Rank	*M* (*SD*)	Mean Rank
Graphical Overview (s)	657 (393)	20.45	725 (408)	22.45
Resources (s)	429 (205)	20.65	432 (136)	22.27
Total Time with Tool (s)	1086 (479)	20.40	1157 (455)	22.50

Navigation behaviour was measured by counting and classifying the opened topics. There was no difference between the groups in the total number of topics opened during the session, $U = 197.5$, $p > .05$, $r = .09$. For every assignment, each topic was classified as a main topic, prerequisite topic, or irrelevant topic. The main topics were the topics that the assignment dealt with. Prerequisite topics were prerequisites of the main topics. All remaining topics were classified as irrelevant. The total number of main, prerequisite and irrelevant topics opened was counted for every user.

Table 2

Number of selected topics.

		With Prerequisites		Without Prerequisites	
		M (*SD*)	Mean Rank	*M* (*SD*)	Mean Rank
Main Topics	Well-Structured	8.45 (5.04)	24.85	6.05 (2.63)	18.45
	Ill-Structured	3.50 (3.47)	20.8	3.32 (2.40)	22.14
Prerequisite Topics	Well-Structured	1.55 (1.23)	24.75	.95 (.72)	18.55
	Ill-Structured	1.35 (1.46)	20.55	1.73 (1.75)	22.36
Irrelevant Topics	Well-Structured	10.65 (4.10)	20.80	12.05 (5.92)	22.14
	Ill-Structured	4.50 (3.09)	19.32	5.95 (4.34)	23.48

Table 2 shows the means, standard deviations, and mean ranks for the number of selected topics. For well-structured problems, participants in the prerequisite condition opened more main topics ($U = 153$, $p < .05$ (one tailed), $r = .26$) and more prerequisite topics ($U =$

155, *p* < .05 (one tailed), *r* = .26), than participants in the control condition. These are both small effects.

For the ill-structured problems, no differences were found between the experimental groups for the number of opened main topics (*U* = 206, *p* > .05 (one tailed), *r* = .06) and prerequisite topics (*U* = 201.0, *p* > .05 (one tailed), *r* = .08). Furthermore, there were no differences between the number of selected irrelevant topics for either structured problems (*U* = 206.5, *p* > .05 (one tailed), *r* = .05) or ill-structured problems (*U* = 167.5, *p* > .05 (one tailed), *r* = .17).

Task Performance

There was no difference in the number of assignments the participants worked on (with prerequisites *Mean Rank* = 23.18, without prerequisites *Mean Rank* = 19.98), *U* = 186.5, *p* > .05, *r* = .02. Participants could get a total of 23 points for the assignments. There was no difference between the quality of the responses produced (with prerequisites *M* = 14.85, without prerequisites *M* = 14.27), *t*(40) = .423, *p* > .05, *r* = .07.

Knowledge

The total number of correct items on the post test was used to determine the knowledge after the session. The maximum score was 21 points. Table 3 shows the results of the post test. Overall, the multiple choice post test did not reveal significant differences between the groups, *U* = 192.5, *p* > .05, *r* = .11. Participants in the control condition did not score better on the factual knowledge questions, *U* = 199.5, *p* > .05 (one tailed), *r* = .08. Participants in the prerequisites condition did not score better on the conceptual knowledge questions, *U* = 194, *p* > .05 (one tailed), *r* = 08.

Table 3

Average and Mean Ranks for scores on Post Test.

	With Prerequisites		Without Prerequisites	
	M (*SD*)	Mean Rank	*M* (*SD*)	Mean Rank
Factual Knowledge	5.90 (1.80)	20.48	6.18 (2.10)	22.43
Conceptual Knowledge	4.10 (1.80)	20.20	4.45 (2.02)	22.68
Total Post Test	10.00 (2.79)	20.12	10.60 (3.75)	22.75

3.4 Conclusion and Discussion

In this study, small effects of the visualization of prerequisite relations in graphical overviews were found: the visualization of prerequisites guided browsing behaviour for well-structured tasks, but not for ill-structured tasks. Neither factual nor conceptual knowledge was influenced by the visualization of prerequisite relationships. Furthermore, the quality of task performance was not influenced by the visualization of prerequisite relationships.

The results for browsing behaviour are in line with the findings of De Jong and Van der Hulst (2002) and McDonald and Stevenson (1998b). De Jong and Van der Hulst found that the structure of the learning domain and the provision of hints both lead to more domain-related browsing behaviour. McDonald and Stevenson found that learners benefit from navigational aids. The results are partially in line with the design principles proposed by Vekiri (2002). The studies reviewed by Vekiri showed that visual cues can guide learners to important sections of graphical overviews. In this study, the visual cues only guided learners when they worked on well-structured tasks, but not on ill-structured tasks. Thus, the characteristics of the task seem to mediate the effects on browsing behaviour. It is remarkable that the visualization of prerequisites did not guide learners for ill-defined tasks. Because graphical overviews are generally associated with ill-structured tasks (Chen & Rada, 1996; Jonassen, 2005), it was expected that providing cues for such tasks would give guidance. It seems that prerequisites only help when learners know the direction in which they should be searching in the graphical overview. If that direction cannot be determined from the task, then prerequisite visualization does not seem to guide navigation.

Although navigation behaviour was influenced for well-structured tasks, no evidence was found to confirm the expectation that the provision of prerequisites leads to more connected understanding and that more connected understanding leads to better task performance. This is consistent with the results of De Jong and van der Hulst (2002). However, it contradicts several review studies showing the effectiveness of graphical overviews (Chen & Rada, 1996; Nesbit & Adesope, 2006). Jonassen (1993) found that the usage of maps was not good for factual recall. In this study, no effects of the visualization of prerequisite relations were found on factual recall.

An explanation of the small effects on learning outcomes might be the time participants actually worked with the tool. Overall, participants used the supportive tool for 18.7 minutes (*SD* 7.7 minutes). On average, they browsed the graphical overview for 11.5 minutes (*SD* 6.6 minutes) and the rest of the time they spent reading supportive material. It seems plausible that the effects of cognitive tools become more distinct when learners use them for a longer period of time and without time pressure for completing the task. Another explanation might be that the size of the graphical overview caused too much disorientation. For the well-structured tasks, visualization of prerequisites might help learners to overcome this problem. However, for ill-structured problems, learners might have too little direction in the map. The question remains of whether the addition of more cues in the overview would help the learner or complicate the overview even more. This study used a relatively authentic learning situation in which learners could use the tool whenever they wished. However, as the learning effects appear to be small, a more controlled setting in which the learners work extensively with the tool for a longer period of time with a focus on understanding the material might be needed. Moreover, the results of Lim, Lee and Grabowski (2008) suggest that learning effects might increase if participants work actively with the graphical overview. Therefore, it is interesting to explore the relation between learner activities and graphical overviews.

Based on the results presented here and the mixed results of previous studies, it is clear that the relationship between graphical overviews and learning is a complex one. The relationship is not only affected by learner characteristics, domain characteristics, prior knowledge of the learner, and the graphical design of the graphical overview, but task characteristics also seem to mediate the effects of cues in graphical overviews. Further research is needed to describe the relationships between graphical overviews and learning in more detail. For now, we can suggest that learning environments that use graphical overviews should be developed in such a way that the overviews can be tailored to the users and the tasks they are performing in order to be most effective. Technology has enabled us to develop new and inspiring ways to visualize and interact with learning material. As the effects of these technologies on actual learning are not yet clear, there is much work to be performed in studying how these new technologies can enhance traditional learning material.

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Chapter 4

Planning and Structural Knowledge[†]

Abstract
Self-regulated learners are expected to plan their own learning. Because planning is a complex task, it cannot be assumed that all learners can plan successfully. In this study, we examined the effects of two planning support tools on the quality of created plans, planning behaviour, task load, and acquired knowledge. Sixty-five participants each worked with two versions of a planning tool. In one version, learning plans were actively constructed by the learners themselves; the other version provided learners with an adaptable computer-generated plan. Results indicated that the quality of learner-created plans was lower than that of computer-generated plans. Furthermore, participants reported a higher task load when they constructed the plans themselves. However, participants gained more structural knowledge about the learning domain when they actively created plans. There was no apparent preference for either of the tools if participants were to create a plan for someone else. However, if they were to use the plan for their own learning, participants preferred to actively create their own plan.

[†] This chapter is based on: Bonestroo, W.J. & de Jong, T. (in press). Effects of planning on task load, knowledge, and tool preference: A comparison of two tools. *Interactive Learning Environments*.

4.1 *Introduction*

Recent attention to lifelong learning and workplace learning has led to renewed interest in types of learning in which learners regulate their own learning process, such as self-directed learning (Ellis, 2007; Loyens, Magda, & Rikers, 2008; Winters, Greene, & Costich, 2008) and self-regulated learning (Azevedo, Moos, Greene, Winters, & Cromley, 2008; Dinsmore, Alexander, & Loughlin, 2008). Regulation includes planning, performing, monitoring, and evaluating the learning process. Although planning is an important phase in the learning process, there is not much research on planning. This is even more remarkable because the creation of a plan is not a trivial process. It requires learners to understand the area of expertise that they wish to acquire, have insight into their own existing knowledge, and have pedagogical knowledge to make informed decisions. In this study, we focus on the planning process in an electronic learning environment.

The Role of Planning in Self-Regulated Learning

Several models describe the self-regulated learning (SRL) process. In their comparison of five well-known models, Puustinen and Pulkkinnen (2001) concluded that all models identified three phases in the self-regulated learning process: the preparatory phase, the performance phase, and the appraisal phase. Goal setting and planning both take place in the preparatory phase. In typical traditional school settings, activities in the preparatory phase are not performed by learners themselves, but by their teachers, schools, or the government. In such situations, decisions about learning goals and plans are made by domain experts. These experts not only know the structure of the learning domain, but can often also rely on their pedagogical expertise (Bransford, 2000). In self-regulated learning, however, these decisions must be made by the learners themselves.

Once learners have selected a learning goal, they need to decide how to reach that goal; in other words, they must create a plan. In any substantial learning domain, advanced knowledge builds on other, more basic knowledge. Therefore, it is often desirable, or even required, that certain topics be understood before other topics are learned. In such cases, these topics have a prerequisite relationship to the other topics. For novices, it can be difficult to determine an appropriate order of topics. Prerequisites can guide them through a complex learning domain (e.g., Hubscher, 2001). Traditional learning materials, such as instructional books, are typically ordered in such a way as to adhere to the prerequisite relationships. Early chapters contain basic knowledge, while later chapters contain advanced knowledge that builds on that basic knowledge. Interactive learning materials, such as websites, simulations, and electronic documents, often are not designed to be accessed in sequential order. Thus, to access the material effectively, someone must decide how to work through it.

Effects of Planning on Learning

Lavery (as cited in Hattie, 2009) studied the effects of meta-cognitive study skills on achievement. She found that strategies addressing the preparatory phase of learning, such as goal setting and planning, were effective for learning. The influence of planning extends beyond the preparatory phase. In the subsequent performance phase, the actual learning activities are performed according to the created plan. Learning without a plan could lead to ineffective learning behaviour. In the appraisal phase, activities from the performance phase are evaluated and learning outcomes are compared to learning goals. Zimmerman (2002) found that learners who set specific goals are more likely to perform regulative processes in the appraisal phase, leading to increased academic success for those learners. He also noticed that novices typically do not spend much time on the preparatory phase. This negatively influences regulative processes in the other learning phases. It is expected that learners who practice self-regulative activities eventually become better self-regulated learners and, therefore, are better prepared for lifelong learning.

Several authors have noted that increased learner control together with non-linear learning environments can lead to problems such as disorientation and cognitive overload (Scheiter & Gerjets, 2007; Shapiro, 2008). To prevent such problems, learner control can be reduced, by such means as letting software make decisions for learners. From a usability perspective, this would reduce users' effort and lead to a more convenient system. However, it might also lead to passive learners who do not become actively involved in the learning material. Mayer (2004) stated that activities in which learners actively select, organize, and integrate knowledge lead to meaningful learning.

In conclusion, it becomes clear from the literature that strategies that aim at the preparatory phase play a crucial role in the learning process. Furthermore, it appears that self-regulated learning generally has a positive inclination with the potential to influence subsequent learning processes. Closer inspection, however, reveals that self-regulation is difficult to perform and can lead to problems. Previous research has addressed processes such as goal setting and self-regulative actions. Although planning seems to play an important role in the learning process according to SRL theories, there is as yet no empirical data on the effects of planning on learning.

Supporting Planning

In his meta-analysis, Hatty (2009) found that learners who use computers learn more effectively when they, and not their teachers, are in control of sequencing and pacing of instructional material. This justifies the use of planning tools in self-regulated learning environments. However, as stated before, planning is difficult and inexperienced learners tend to make wrong decisions during the learning process. For example, Bell and Kozlowski (2002) stated that learners typically "do not make good instructional use of the control they are given" (p. 267). Support may help to overcome this problem. Azevedo et al. (2008) compared self-regulated learners to self-regulated learners who were supported by a human regulating agent. They found that 'externally' self-regulated students gained more declarative knowledge and developed more advanced mental models. Learners in the self-regulated condition used ineffective strategies more often and did less monitoring of the process. According to Bell and Kozlowski (2002), study and practice, self-regulation, acquired knowledge, and performance can all be enhanced by adaptive guidance. Furthermore, novice learners do not always perform regulative activities spontaneously in non-experimental settings (Azevedo et al., 2008; Zimmerman, 2008). Explicitly supporting the planning process might also invoke regulative activities that would not have been performed otherwise.

The creation of a learning plan is a typical example of an ill-structured problem (Jonassen, 2000); there are multiple paths to reach one learning goal, and there are no clear rules for comparing the different paths. Solving ill-structured problems can be supported by visually representing the problem space. Previous research has shown that expert instructors can be supported in course design with graphical overviews (e.g., Coffey, 2005). Kennedy et al. (2000) developed a personal learning planner to support learners. Their tool visualized the learning domain and learning goals with a variety of representations, including lists, concept maps, and tables. They did not report empirical results for learners actually working with their tool. It is unclear whether novice learners can also design their own learning process with such tools and what the effects on learning might be.

Graphical Overviews

Graphical overviews can visualize the interrelated character of learning domains. Such visualizations show the topics and relationships and enable learners to grasp the structure of a learning domain, without being exposed to all of the detailed learning material. There are many types of graphical overviews, such as semantic networks (Quillian, 1967), graphic organizers (Winn, 1991), concept maps (Novak & Cañas, 2006), knowledge maps (O'Donnell, Dansereau, & Hall, 2002), and topic maps (Dicheva & Dichev, 2006). These representations all have in common the use of labelled nodes to represent concepts and links between the nodes to represent relationships between concepts. Traditionally, overviews are static pictures, composed of boxes, lines, and labels. However, current computer technology enables us to display overviews that change dynamically over time. In this way, graphical overviews can adapt, for example, to actions of users or to the current knowledge state of individual users (e.g., Brusilovsky, 2001).

Research shows that, in general, graphical overviews are effective tools for learning. In their meta-analysis of fifty-five studies, Nesbit and Adesope (2006) found that creating, modifying, and reading graphical maps all had positive effects on learning. McDonald and Stevenson (1998) found that graphical maps improved text comprehension and led to better knowledge compared to lists. All seven studies reviewed by Chen and Rada (1996) supported the hypothesis that graphical maps that visualize the organization of a hypertext have significant positive impact on the usefulness of a hypertext system. O'Donnell, Dansereau and Hall (2002) reviewed literature on knowledge maps and found that learning from maps is enhanced when maps are designed according to Gestalt principles of organization, such as proximity and similarity. The proximity principle states that elements that are placed close to each other are interpreted as related, and the similarity principle states that elements that share visual characteristics are interpreted as belonging together.

Navigational aids and support can direct learners' behaviour and this can benefit the learning process (McDonald & Stevenson, 1998). De Jong and Van der Hulst (2002) found that the structure of the learning domain and the provision of hints both led to more domain-related browsing behaviour. The studies reviewed by Vekiri (2002) showed that visual cues can guide learners to important sections of graphical overviews.

Planning with graphical overviews could have additional benefits over planning in general. Providing learners with an explicit visualization of a learning domain can help learners to get an overview of available information. By showing how new knowledge is related to prior knowledge, visualizations provide anchors for attaching new knowledge, leading to meaningful learning (Ausubel, Novak, & Hanesian, 1978). Explicit visualization of the structure of knowledge can trigger learners to restructure their own knowledge. Activation of prior knowledge is another important activity in the learning process (Azevedo et al., 2008). Because an overview shows all topics in a domain without showing the learning material, learners can quickly scan topics they have already studied before and see how those topics are related to new topics. In this way, visualizations help in activating prior knowledge.

Research Questions

In SRL theories the preparatory phase of learning is an important phase in the learning process. Previous studies have found positive effects for goal setting and self-regulative activities. However, there is as yet no empirical evidence on the effects of planning on learning. As self-regulated learning gains more attention, we think it is important to better understand how the planning process should be supported. The goal of this study was to examine the amount of control learners should have over the planning process in an e-learning environment; we wanted to know whether learners should create their own plan or whether the plan should be presented to the learners. Two tools were developed for this study. In one version, the planning tool only had a supportive role, and participants were actively involved in the planning process; in the other version the tool provided participants with an adaptable plan at the start of the process. For both tools, we measured quality of created plans, browsing behaviour, experienced task load, recall of structural knowledge, and recall of factual knowledge. With both tools, participants had to plan learning and inspect elements of the plan in the corresponding graphical overview.

The quality of learning plans was determined based on instructional information for the learning domains. The instructional information consisted of the prerequisite relations between the topics in the model. As the automatic generation of plans was based on that information, automatically generated plans were always correct. During active construction of a plan, learners received adaptive feedback about their current plan. Because of this support, it was expected that the quality of their plans would be equal to the quality of the automatically generated plans. As planning is a meta-cognitive process in which learning material is actively selected and organized, it was expected that learners would gain knowledge from the planning process itself. As planning takes place on a high abstraction level, it was expected that learners would gain structural knowledge. Moreover, it was expected that learners who were actively involved in the process would make more use of the provided support, and therefore would show more domain related browsing behaviour. Because planning requires both cognitive resources and time, it was expected that learners who created a plan would have less time and resources to inspect the detailed information in the plans. Accordingly, we expected that this would hinder the acquisition of factual knowledge. As actively involving learners in the process can lead to increased motivation for learning, it was expected that learners would prefer to use the tool in which they actively constructed the plan for their learning.

4.2 *Method*

Design

In this study we compared two computer software tools designed to generate plans for learning: a tool where the computer generated the plan (CG-tool) and a tool where learners actively created plans (LG-tool). We applied a within-subjects experimental design in which all participants worked with both tools twice (CG-LG-CG-LG or LG-CG-LG-CG) and learned in four different domains (explained in more detail in the Materials section). To compensate for carry-over effects, the order of the tools and the order of the domains were counterbalanced, resulting in eight different sequences of tools used and domains encountered. Table 4 lists the combinations of tools and domains.

Materials

All software used in the experiment was implemented with Adobe Flex, resulting in an Adobe Flash web application that was accessible with a browser. All measurements and forms were integrated in the software and administered electronically. A total of four learning domains were used. Two domains were about data analysis. One focussed on parametric statistical tests, such as ANOVA and linear regression. The other addressed non-parametric statistical tests, such as the sign test and rank correlation coefficients. The other two domains were about computer science. One addressed scheduling and the other processes management. To avoid confusion, all domains were selected so that they did not overlap with any of the other domains.

Table 4
Sequences of tools and domains used in study design.

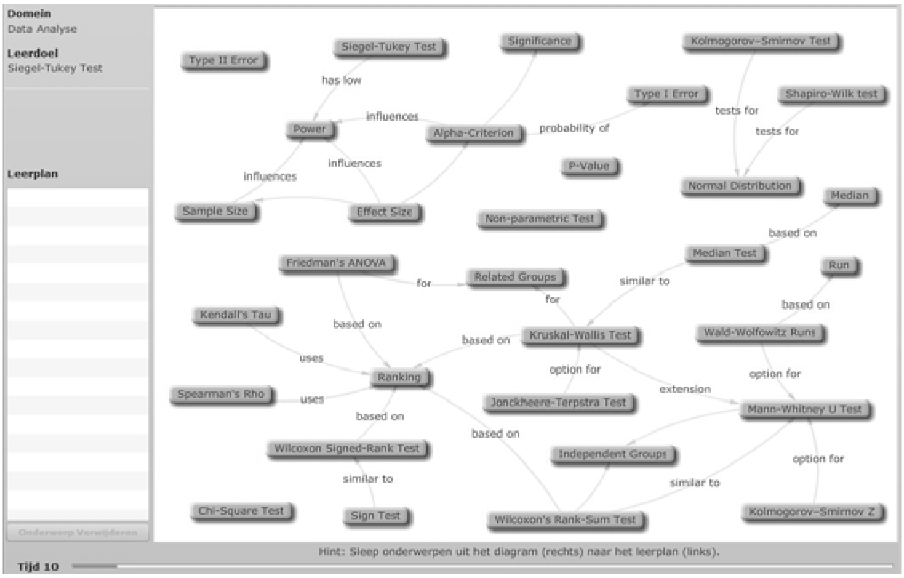
	First Trial		Second Trial		Third Trial		Fourth Trial	
group	Tool	Domain	Tool	Domain	Tool	Domain	Tool	Domain
1	LG	DA1	CG	DA2	LG	CS1	CG	CS2
2	CG	DA1	LG	DA2	CG	CS1	LG	CS2
3	LG	DA2	CG	DA1	LG	CS2	CG	CS1
4	CG	DA2	LG	DA1	CG	CS2	LG	CS1
5	LG	CS1	CG	CS2	LG	DA1	CG	DA2
6	CG	CS1	LG	CS2	CG	DA1	LG	DA2
7	LG	CS2	CG	CS1	LG	DA2	CG	DA1
8	CG	CS2	LG	CS1	CG	DA2	LG	DA1

Note. DA1: First Data Analysis domain, DA2: Second Data Analysis domain, CS1: First Computer Science domain, CS2: Second Computer Science domain.

Figure 20 shows the planning tool. With the LG-tool, learners had to actively construct a learning plan. With the CG-tool, the computer provided them with such a plan. The only difference between the tools was that the LG-tool started with an empty plan and the CG-tool started with a completed plan. Plans were edited by dragging and dropping elements from the graphical overview (on the right) into the learning plan (on the left). Elements in the plan could be reordered or removed from the plan. Graphical feedback was provided with arrows that indicated prerequisite relations between topics. The lower part of the screen contained adaptive textual feedback. To prevent users from missing the feedback, dynamic visual effects were used. The graphical overviews of the domains were designed according to the proximity principle described by O'Donnell, Dansereau, and Hall (2002).

Participants

Participants were 65 first-year students of behavioural science, 54 females and 11 males. Their average age was 20 years (*SD* = 2.01). Students had not yet encountered the presented learning domains in their curriculum; therefore, it was assumed that they had no prior knowledge about the learning domains used in the study. Participants received the tools and learning domains in one of the eight orders described in the Design section. All participants received both tools twice and each learning domain once. Participants received credits for participating.



Hint: Sleep onderwerpen uit het diagram (rechts) naar het leerplan (links).

Figure 20. The planning tool with the learning goal (Leerdoel) and learning plan on the left and the graphical overview of the learning domain on the right.

Measurements

The dependent variables were cognitive load, structural knowledge, factual knowledge, browsing behaviour, and plan quality. Cognitive load was measured with an adapted version of the NASA Task Load Index (TLX) developed by Hart and Staveland (1988). The TLX combines ratings, weights, and results in one score. The original version uses 6 scales and 15 pair-wise comparisons between the scales. In this experiment, the scale 'physical demand' was removed from the test because physical demands were not important for this study. Furthermore, the removal of one scale reduced the time required to fill-in the measure considerably. In this study, the TLX was used with the 5 remaining scales and 10 pair-wise comparisons.

The knowledge that resulted after the planning process was measured with two types of knowledge tests: a structural and a factual knowledge test. Structural knowledge refers to the structure of the domain and factual knowledge refers to textual information that was contained in the models. Structural knowledge was tested with closed questions. Participants were asked to indicate which concepts were prerequisites for other concepts. Factual knowledge was tested with multiple-choice questions. For every domain, there were four structural questions for which participants could receive a maximum score of 16 points, and four factual questions for which they could get four points. Both tests were administered directly after completing a distracter task.

Browsing behaviour was measured by analyzing the log files. For every learning domain and learning goal, topics were classified as either relevant or irrelevant to that goal. Detailed information about topics was shown in tooltips. Tooltips appeared as users hold their mouse pointer above a certain topic. The topics and amount of time for the display of tooltips were recorded in log files.

In both tools, participants received an editable learning plan. The CG-tool provided the correct plan at the start, whereas the LG-tool provided an empty plan. Thus, learners had to construct the plan from scratch with the LG-tool. Plans were automatically scored as either correct or incorrect. Scoring was based on the instructional information contained in the learning domains. Plans were considered correct if they contained the prerequisite topics and did not contain irrelevant topics for the given learning goal.

General data such as age and gender and the preferences for the tools were collected with an electronic questionnaire. To measure preferences, participants were asked which tool they would prefer if they were to create a learning plan for themselves and for someone else. Furthermore, they were asked which tool would result in the best learning outcomes for structural and factual knowledge.

Procedure

Participants were tested in the computer laboratory in groups of ten to twenty persons. Sessions took one hour to complete. At the start of the session, the experimenter explained the procedures to the whole group. Then, participants logged in, read the instructions individually, and did a practice session with the software. After that, the measurements were explained and participants completed a sample structural and factual knowledge test. Accordingly, participants knew what kind of questions to expect. The practice session took about 15 minutes in total. Then, each participant worked with all four domains. They received two tasks in every domain. A learning goal was provided for every task. Based on that learning goal, participants either received a plan to achieve that goal, or they had to create a plan with assistance of the tool. In both cases they were instructed to inspect the plan and the items in the plan. Each plan consisted of approximately ten topics from the domain and participants worked exactly three minutes with a plan. Within those three minutes, participant had to both create and inspect the plan. After every two tasks they were asked to indicate their task load by completing a TLX. Because the measurement of task load was an attention-demanding task it also functioned as a distracter task for the knowledge tests. Directly after completing the TLX, participants received structural and factual knowledge tests for that domain. After the four domains were completed, participants were asked to complete the questionnaire that addressed general data such as gender, age, and their preferences.

Analysis

We used both parametric and non-parametric tests to test our research hypotheses. When a data distribution violated parametric assumptions, a Wilcoxon signed rank test was used and the *T* value and medians are reported. Otherwise, a paired samples t-test was used, and the *t* value and means are reported. Directional hypotheses were analyzed using one-tailed and non-directional hypotheses with two-tailed tests. There were two pairs of questions measuring preferences. Both pairs were analyzed with a McNemar-Bowker test to test whether there were reliable differences between the provided answers (Bowker, 1948). All results are reported at a .05 level of significance. An effect size estimate, *r*, is reported for each performed test with significant results. Effect size estimates were calculated using to the techniques proposed by Rosenthal (1991).

4.3 *Results*

Two participants did not create any correct plans with the LG-tool. Because we can reasonably assume that these participants either did not understand the assignment or were not seriously participating in the study, and because their results were outside the range of three times the standard deviation, their results were removed from the data. All analyses were performed on the remaining 63 participants.

Quality of Plans

We expected that there would be no differences in quality for plans from both tools. Analysis of the plan quality showed that participants constructed more correct plans with the CG-tool (*Mdn* = 4) than with the LG-tool (*Mdn* = 4), $T = 25.50$, $p < .05$, $r = .37$.

Knowledge and Task Load

As expected, participants had more structural knowledge after working with the LG-tool than with the CG-tool. Participants scored significantly higher on the structural questions with the LG-tool, (*Mdn* = 25) than with the CG-tool (*Mdn* = 23), $T = 25$, $p < .05$ (one tailed), $r = .16$. Participants were expected to score higher on the factual questions with the CG-tool. This was not confirmed by the data. Participants did not score higher on the factual questions with the CG-tool (*Mdn* = 2) compared to the LG-tool (*Mdn* = 2), $T = 24$, $p > .05$ (one tailed). As expected, participants reported a significantly higher task load when they worked with the LG-tool ($M = 129.06$, $SD = 30.79$) than when they worked with the CG-tool ($M = 123.44$, $SD = 29.52$), $t(62) = 1.98$, $p < .05$ (one tailed), $r = .28$.

Browsing Behaviour

It was expected that participants with the CG-tool would spend more time on reading learning material texts, because they did not have to construct the plan first. However, participants did not spend more time on reading the text with the CG-tool (*Mdn* = 337.16 seconds) than with the LG-tool (*Mdn* = 342.67), $T = 29$, $p > .05$ (one tailed). Thus, participants spent approximately the same amount of time on reading text with both tools.

Table 5

Average times for reading relevant and irrelevant topics with both tools.

	Relevant topics read (s)		Irrelevant topics read (s)	
	M	*SD*	*M*	*SD*
CG-tool	248.78	120.43	84.63	98.61
LG-tool	261.53	104.49	80.41	93.16

Table 5 displays the average times participants spent on reading relevant and irrelevant topics. The total time in each condition (each row) was 720 seconds. Participants could read text from relevant topics, irrelevant topics, or not read text at all. To test whether there were effects of the tool on reading times, a two-way repeated measures ANOVA was performed. There was no main effect for tool use, $F(1, 62) = 1.36$, $p > .05$. Furthermore, there was no interaction effect between the tool used and the relevance of the read texts, $F(1, 62) = 2.47$, $p > .05$.

Preferences

Participants were asked from which tool they thought they had gained most structural and factual knowledge. The results for both questions are summarized in Table 6. There was a significant difference between the participants' answers for structural and factual knowledge, McNemar-Bowker $\chi^2(6, N = 63) = 31.62$, $p < .05$. The majority of the participants (87%) thought that they had gained more structural knowledge in the LG condition. For factual knowledge, however, there was no apparent preference for either of the conditions. Participants were also asked which tool they would prefer in two situations. The results are listed in Table 7.

Table 6

Perceived knowledge for factual and structural knowledge.

		Factual knowledge				
	Tool	Learner Generated	Computer Generated	No difference	Don’t know	Total
Structural knowledge	Learner Generated	22	24	6	3	55 (87%)
	Computer Generated	2	2	0	0	4 (6%)
	No difference	0	1	0	0	1 (2%)
	Don’t know	0	2	1	0	3 (5%)
	Total	24 (38%)	29 (46%)	7 (11%)	3 (5%)	63 (100%)

Note. The cells represent a combination of the answers for factual and structural knowledge. For example, 24 participants thought that they learned most factual knowledge from the CG-tool and most structural knowledge from the LG-tool.

There was a significant difference between the participants’ answers for the two hypothetical situations, McNemar-Bowker $\chi^2(3, N = 63) = 8.15, p < .05$. When participants would have to make a plan for their own learning, most participants (71%) would prefer the LG-tool to the CG-tool. However, when participants would have to make a learning plan for someone else, there was no apparent preference for either of the tools.

Table 7

Preferences for tools.

		Learning plan created for self			
	Preferred Tool	Learner Generated	Computer Generated	No Preference	Total
Learning plan created for Others	Learner Generated	23	4	3	30 (48%)
	Computer Generated	14	5	4	23 (37%)
	No Preference	8	2	0	10 (16%)
	Total	45 (71%)	11 (17%)	7 (11%)	63 (100%)

4.4 Conclusion and Discussion

In this study, we compared two computer software tools designed to generate plans for learning: a tool where the computer generated the plan (CG-tool) and a tool where learners actively generated their own plans (LG-tool). We found that learners performed better on the structural knowledge test when they worked with the LG-tool than when they worked with the CG-tool. Thus, when learners were actively involved in the planning process they gained more structural knowledge, compared to when they were more passively working with the planning tool. Because planning sets the stage for the subsequent phases, this initial gain in knowledge might give them a head start in the whole learning process. In line with the results of the knowledge test, participants thought that they had gained more structural knowledge while working with the LG-tool, compared to working with the CG-tool. No difference was found for factual knowledge. Learners did not gain more factual knowledge when they worked with the CG-tool, compared to the LG-tool. In line with the results from the knowledge test, learners had no pronounced idea about the tool in which they gained most factual knowledge. As expected, participants reported a higher task load while working with the LG-tool compared to working with the CG-tool. Participants created lower quality plans with the LG-tool. This was unexpected, because adaptive support was assumed to guide learners through the planning process. Finally, participants preferred to use the LG-tool, but only when planning for their own learning process. When they were to create a learning plan for someone else, they had no pronounced preference. This could indicate that they perceived active planning as a meaningful activity for the learning process.

In general, these results are consistent with the theories of active learning that posit that people learn by doing. Considering the distinction put forward by Mayer (2004), the activities that participants performed during planning can be classified as cognitive activities and, therefore, should support the learning process.

Results from this study underline statements made by Shapiro (2008), who concluded that tools that are usable are not always good for learning. From a usability perspective, the CG-tool outperformed the LG-tool, because it resulted in lower task load. If we assume that the improved structural knowledge from the planning process leads to increased learning outcomes for the whole learning process, the LG-tool was better for learning than the CG-tool. Our findings suggest that computers can help self-regulated learning by supporting learners. However, taking over the process could lead to passive learners and does not support learning. Therefore, the application of computer-supported regulation in learning environments should be carefully considered.

The results show that there was a difference in the quality of the plans. The quality of the plans created with the LG-tool was lower than the quality of the plans created with the CG-tool. However, structural knowledge was higher with the LG-tool. This raises an interesting point. Although quality of the plans was lower when they were actively created, participants gained more (correct) structural knowledge by doing so. It would be expected that if learners received more instructions on how to create correct plans, the knowledge effects might be even stronger. There are several solutions to prevent learners from making incorrect plans. In the current study we used a technical solution, in which the support was build into the tools. Another approach is to train learners on how to make a plan and how to perform self-regulative learning processes. Greiner and Karoly (1976) found that learners who received training in self-monitoring, self-reward, and planning outperformed learners who did not receive such training.

In this study, the differences in knowledge cannot be explained by the duration of exposure to the material. All participants had exactly the same amount of time to work with the tools. Furthermore, there was no difference in the time that was actually spent on inspecting the plans. It was expected that learners would spend more time reading the factual information with the CG-tool, because they did not have to create the plan. However, the results do not support this. Based on the studies performed by McDonald and Stevenson (1998), and de Jong and van der Hulst (2002), it was expected that participants with the LG-tool would make better use of the hints and show more domain-related browsing behaviour. However, the results do not reveal different behaviours for the tools.

There are some aspects we should keep in mind in interpreting the findings from this study. First, this study focussed on effects of planning processes. The actual performance phase of learning, which normally follows the preparatory phase, was not studied in this experiment. Only knowledge gained during planning was measured. In this study a significant effect of the creation of plans on structural knowledge was found. Although the effect size was small, the question remains whether this small effect in the initial phase of learning eventually yields larger gains in the overall learning process. SRL theories suggest that planning influences all phases of the learning process. Based on our findings, it would be interesting to study the results of planning in the actual performance phase. Second, the scores on the factual knowledge test were lower than expected. The difficulty of the questions might have resulted in a floor effect for the factual knowledge test. Third, it is not known whether the initial quality of the plans is a good predictor for the eventual learning outcomes. If a planning tool is used in a real learning setting, learners can update their plan as they gain knowledge and insight in the learning domain. Therefore, an incorrect initial learning plan might not have negative consequences for learning. Future research should include the entire process, in which learning plans are created and updated as learning proceeds. Fourth, the quality of the plans was determined based on the pedagogical information for the domains. Sometimes, instructional information for the domains is complex and difficult to express. For example, in the current domains, expressing that superficial knowledge of one topic was needed to understand another topic was not possible. The quality of suggestions made by automatic systems depends on the quality and expressiveness of the instructional models used. More advanced models can contain more details. However, in practice, such models are also more difficult to build and maintain. One of the interesting points of the tool used in this study was that the planning tool was simple and effective.

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Chapter 5

Does Planning Support Learning? [‡]

Abstract

Is actively planning one's learning route through a learning domain beneficial for learning? Moreover, can learners accurately judge how much planning has been beneficial for them? In this study, the effects of active planning on learning were examined. Participants received a tool in which they created a learning plan before accessing the learning material. As a control condition, participants worked with a tool in which planning was performed automatically. Eighty-three participants performed learning sessions with both tools over a series of topics in statistics. Results indicate an inconsistency between judgment of learning and actual learning outcomes. Although the tools influenced the learning process and participants thought they had learned most when they actively created a plan, knowledge tests showed no differences between the tools. Results are discussed in the light of Winne and Hadwin's model of self-regulated learning.

[‡] Based on Bonestroo, W.J. & de Jong, T. (2010). The planning illusion: Does active planning support self-regulated learning as well as we think? Manuscript submitted for publication.

5.1 *Introduction*

Planning is an essential but difficult step in the learning process. In traditional educational settings, planning activities are typically not performed by learners themselves, but by others, such as teachers, schools, or educational publishers. In such situations, decisions about learning plans are made by domain experts, who not only know the structure of the learning domain but who also often can rely on their pedagogical background knowledge. In self-regulated learning (SRL), however, learners are responsible for their own learning, and are expected to make such decisions. In making these decisions, learners can be supported, for example by a computer-based planning tool. When learners plan their own learning, this changes their learning process and this might influence learning outcomes of that process. In this study, we tested whether active planning had positive effects on learning.

What is Planning?

Planning is performed as one of the first activities in the learning process. It is considered an essential activity and several authors have suggested its potential to positively influence SRL (e.g., Azevedo, Guthrie, & Seibert, 2004; Boekaerts, Pintrich, & Zeidner, 2005; Hattie, 2009; Zimmerman & Schunk, 2001). To distinguish planning from other self-regulatory activities, Azevedo, Guthrie, and Seibert (2004) developed a coding scheme, in which they described that "[a] plan involves coordinating the selection of operators" (p. 292). Such operators are information-processing activities that learners can perform during learning, such as searching, monitoring, assembling, rehearsing, and translating information. In their more general approach to planning, Miller, Galanter, and Pribham (1960) defined plans as "any hierarchical process in the organism that can control the order in which a sequence of operations is to be performed" (p. 16). These authors focus more on the structure and sequence of operations. According to these two definitions, planning addresses the selection of operators and the order in which they are executed. In this definition, learners have to decide on what type of operations they are going to perform; whether they are going to read, practice, rehearse, etc. Planning can also include aspects such as available time, available material, required effort, and issues with regard to help seeking (Zimmerman, 2008). In authentic SRL settings, learners generally have to consider such factors when they make decisions about their own learning. Another view on planning concerns the selection and sequencing of content. In the literature, this is often referred to as learner control (Lawless & Brown, 1997; Scheiter & Gerjets, 2007). In such situations, learners do not have to decide the activities to perform but only the content to use and in which order, leading to a less demanding way of planning the learning process. In this study we focus on the latter type of planning, the sequencing of content.

Self-Regulated Learning and Planning

To explain the effects of planning on learning, we used Winne and Hadwin’s (1998) SRL model as theoretical framework. Their model integrates contextual, cognitive, and motivational aspects, and explicitly describes which activities in the learning process are performed. Winne and Hadwin described SRL as a process with three required phases and one optional fourth phase. The required phases are: 1) task definition, 2) goal setting and planning, and 3) studying tactics. Planning takes place in the second phase and the actual learning process is performed in the third phase. The optional fourth phase is called adaptations to metacognition. Although Winne and Hadwin described their model as recursive and weakly structured, meaning that learners can move back and forth through the model, they assumed that learners generally proceed through the identified phases. In each of the four phases, learners perform cognitive activities resulting in tangible products, such as created learning plans or summaries of the learning material, but also in non-tangible products, such as cognitive structures in the minds of learners. Winne and Hadwin’s comprehensive description of processes and phases allows for a detailed look at how the various aspects interact (Greene & Azevedo, 2007).

Planning and Learning

Planning is an activity in which learners actively process high-level information about the learning domain and this could lead to improved learning and knowledge. However, not all activities that learners undertake lead to knowledge. Mayer (2004) distinguished cognitive from behavioral activities. Learning only takes place when learners perform cognitive activities, for example, when they actively select, organize and integrate knowledge. This was recently demonstrated in the meta-study documented in Lavery’s PhD dissertation (as cited in Hattie, 2009, p. 189-190). Lavery compared the effects of several study strategies on achievement and she found the largest effect sizes for strategies aiming at the preparatory phase, such as goal setting, planning, self-instruction, and self-evaluation. She suggested that those positive effects could be caused by the active approach that learners took to the learning task. Lavery also found that the reorganization of learning material by learners was a highly effective strategy. Planning is such a cognitive activity in which learners actively work with and reorganize learning material. During planning, learners actively process high-level, abstract information, and this can help building structural knowledge. Because such knowledge can be used for chunking information and can help to sort and interpret new information, improved structural knowledge at the start of the learning process would be beneficial for the whole learning process.

The Effects of Planning on Motivation and Evaluation of Learning

Planning is not only supposed to positively influence learning directly, but it also is expected to influence other factors that in their turn act upon the learning process: motivation and evaluation of learning.

In their literature review, Scheiter and Gerjets (2007) examined the relationship between one specific task condition, learner control, and motivation. They reported that learners who had more control over their learning environment were more motivated and interested. Cordova and Lepper (1996) even found that students who only received control over irrelevant parts of the learning environment not only showed increased motivation, also their depth of engagement in learning was increased, they learned more in a fixed time period, and their perceived competence and levels of aspiration increased.

Planning is also expected to influence the evaluation of the learning process. In SRL literature, evaluation of one's learning is referred to as judgment of learning (JOL). To accurately perform JOL, learners require adequate task definitions and learning plans to evaluate their outcomes. Greene and Azevedo (2007) summarized studies on JOL and found that learners' judgments were not always accurate. During evaluation, learners compare their actual performance to their standards. Standards used in the third phase of SRL are based on the operations and products from the first and second phase. Thus, learning goals and plans form the standards for learning. Although evaluations take place in every phase of the learning process, in the current study, we only focus on the evaluation of the third SRL phase, studying tactics, where the actual learning processes are performed.

Prior Knowledge and Planning

An important condition for learning is prior domain knowledge. Research shows that higher prior knowledge predicts better SRL performances. Moos and Azevedo (2008c) provided a possible theoretical explanation of the influence of prior knowledge on SRL. They speculated that learners with limited prior knowledge required more processing capacity to process learning material. Because learners have a limited processing capacity, they had less capacity available for regulative activities. The authors suggested that when learners have little prior knowledge, they should be supported in their regulative activities to prevent overloading their cognitive systems. This is similar to the theoretical work by Lawless and Brown (1997), who examined literature on learner control and navigation in multimedia learning environments. They described several studies in which increased learning control improved learning. However, they also described that when learners had low levels of prior knowledge, or when learners did not have clear learning goals in the learning environment, unrestricted learning control could impede learning.

Supporting and Stimulating Planning

If planning is beneficial for the learning process one might expect that learners will engage in planning processes spontaneously. Empirical research shows, however, that not all learners perform such activities, but also that such activities can be stimulated. For example, Azevedo, Moos, Green, Winters, and Cromly (2008) provided students with a human tutor who facilitated self-regulative learning. They found that students performed significantly more planning activities when they were supported by the tutor. Moos and

Azevedo performed two studies in which students were provided with conceptual scaffolds (2008a, 2008b). Conceptual scaffolds were guiding questions that were expected to help understanding the relationship between different concepts in the learning domain. In both studies, they found that participants who received scaffolds performed more planning activities than participants who did not receive them. This is in line with the results of Manlove, Lazonder and de Jong (2009), who performed three studies in which they provided learners with a support tool called the process coordinator. This tool contained goal-lists, hints, prompts, cues, and templates to support cognitive regulation for a modeling task. They found that students performed significantly more planning activities with the tool than without it. Although these studies addressed different types of planning and support, they all demonstrated that support stimulated important SRL activities such as planning.

The studies above show a clear relationship between the provision of support tools and the number of performed planning activities. However, the effects of support tools on learning outcomes, the next phase in Winne and Hadwin's model, is confusing. In one of the studies performed by Moos and Azevedo, positive correlations were reported between the number of planning activities and knowledge (2008b) and in their other study, learning outcomes were not measured (2008a). Manlove, et al. (2009) reported no relation between tool use and learning outcomes in two of their studies and a negative relation in one of them. An explanation of this finding is that the type of planning was cognitive demanding for the learners. In the process coordinator, learners were expected to choose what type of activities to perform, and this might have been too complex and difficult for them.

Summarizing, according to SRL literature, planning is generally considered an important part of the learning process with the potential to positively influence learning. However, claims about positive effects of planning on learning are not fully backed up by empirical research and we have found no experimental research in which only the planning process was varied. Apparently, different types of planning have different effects on the learning process. Empirical findings for the effects of planning suggest that planning for learners with little prior knowledge should be supported and kept simple.

Research Questions

In this study, we examined whether actively planning one’s learning route through a learning domain was beneficial for learning. In terms of Winne and Hadwin’s model, we examined the effects of operations (planning) in the second SRL phase on the products (learning outcomes) of the third SRL phase. In a previous study (Bonestroo & De Jong, in press), we examined effects of active planning on products (knowledge) of the second phase. We measured knowledge directly after planning and before the actual learning had started. In that study, we compared the effects of two tools on knowledge, task load, and tool preference. In one tool, learning plans were actively constructed by the learners, and in the other tool, plans were automatically constructed and presented to the learners. Results indicated that actively creating one's plan resulted in higher reported task load, but also in more structural knowledge about the learning domain. There was no significant difference for factual knowledge, so the gain in structural knowledge was not at the expense of factual knowledge. In the current study, we examined whether those positive effects for structural knowledge in the second phase, propagate to the learning outcomes of the third phase. We tested whether learners learn more when they actively create their own planning, compared to when the planning is automatically created by the computer. Therefore, we set up an experiment in which we compared the effects of two planning tools: the CG-tool and the LG-tool. In the CG-tool, the computer generated plans and in the LG-tool learners actively generated their plans. To measure learning outcomes, we distinguished three types of knowledge: factual, conceptual, and structural knowledge. These types are described in the 'method' section. Besides knowledge, we used self-report measures to examine task load, motivation, and preferences. Furthermore, we analyzed log files to identify patterns in the activities that participant performed in the tools.

We expected that active planning would not hamper the acquisition of factual knowledge and that, after the whole learning session, structural knowledge would be better with the LG-tool. Because structural knowledge can facilitate learning, we also expected that conceptual knowledge would be better with the LG-tool. Furthermore, it was expected that participants would be more motivated when working with the LG-tool, because they would have more control over the learning process. Finally, learners were expected to report a higher task load working with the LG-tool than with the CG-tool, because the whole learning process (planning and performance) was expected to be more demanding with the LG-tool than with the CG-tool.

5.2 *Method*

Material

To let participants actively plan their learning, a tool (the LG-tool) was developed that aimed at supporting concise learning sessions. The tool contained learning material and a graphical overview that displayed the topics of the learning material, the relationships between those topics, and instructional information about the prerequisites in the learning domain. With the tool, participants could create a plan, and the learning material was ordered and presented according to that plan. Learning plans were defined as sequences of topics from the learning domain. Before using the plans for the learning process, the tools checked whether the plans included all required topics for that learning goal. As long as the plans were not approved by the tools, the tools provided support to complete the plan. Accordingly, all participants ended up with the same topics in their plans. Only the order of the topics in the plan varied. Thus, participants had sequence control over the learning process, but not content-control. Aspects, such as available time and material, were controlled in the experiment. Participants did not consider such aspects in the planning process and could focus on the learning material.

To create and check learning plans, the tool used the prerequisite relationships available in the learning domain. *Figure 21* shows a screenshot of the planning tool. The left column shows the current learning goals (Leerdoelen) and the learning plan (Leerplan). The right part of the figure shows the graphical overview. The CG-tool, that was used as the control condition, was exactly the same as the LG-tool, except that the tool automatically created the learning plan and presented the plan to the participants.

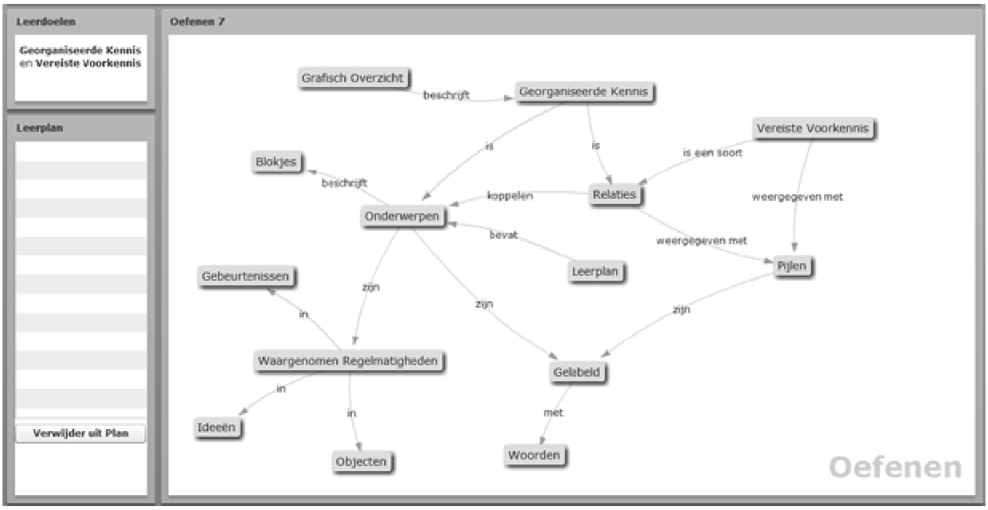
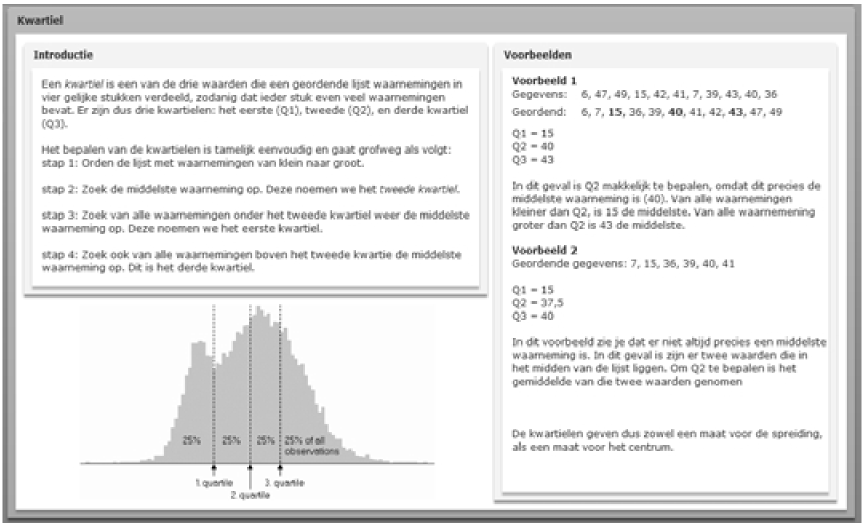


Figure 21. Planning Tool with on the left the learning goals and learning plan and on the right the graphical overview of the learning domain.

The learning domain was introductory statistics. Two topics within statistics were used: measures of center and spread, and correlation and regression. For every topic we identified 25 key concepts and for every concept, a page with learning material was composed. *Figure 22* shows an example of such a page with learning material. The pages had approximately 250 words and 1 or 2 images illustrating the concept. Learning material was taken from two introductory statistics books. We used the first two chapters from Discovering Statistics using SPSS (Field, 2009) and the first two chapters from the Dutch version of Introduction to the Practice of Statistics (Moore & McCabe, 1997).



Kwartiel

Introductie

Een *kwartiel* is een van de drie waarden die een geordende lijst waarnemingen in vier gelijke stukken verdeeld, zodanig dat ieder stuk even veel waarnemingen bevat. Er zijn dus drie kwartielen: het eerste (Q1), tweede (Q2), en derde kwartiel (Q3).

Het bepalen van de kwartielen is tamelijk eenvoudig en gaat grofweg als volgt:
stap 1: Orden de lijst met waarnemingen van klein naar groot.

stap 2: Zoek de middelste waarneming op. Deze noemen we het *tweede kwartiel*.

stap 3: Zoek van alle waarnemingen onder het tweede kwartiel weer de middelste waarneming op. Deze noemen we het eerste kwartiel.

stap 4: Zoek ook van alle waarnemingen boven het tweede kwartie de middelste waarneming op. Dit is het derde kwartiel.

Voorbeelden

Voorbeeld 1
Gegevens: 6, 47, 49, 15, 42, 41, 7, 39, 43, 40, 36
Geordend: 6, 7, **15**, 36, 39, **40**, 41, 42, **43**, 47, 49

Q1 = 15
Q2 = 40
Q3 = 43

In dit geval is Q2 makkelijk te bepalen, omdat dit precies de middelste waarneming is (40). Van alle waarnemingen kleiner dan Q2, is 15 de middelste. Van alle waarnemening groter dan Q2 is 43 de middelste.

Voorbeeld 2
Geordende gegevens: 7, 15, 36, 39, 40, 41

Q1 = 15
Q2 = 37,5
Q3 = 40

In dit voorbeeld zie je dat er niet altijd precies een middelste waarneming is. In dit geval is zijn er twee waarden die in het midden van de lijst liggen. Om Q2 te bepalen is het gemiddelde van die twee waarden genomen

De kwartielen geven dus zowel een maat voor de spreiding, als een maat voor het centrum.

Figure 22. Sample content for topic Quartile (Kwartiel) with an introductory text, a graphical representation and two examples of the topic.

To create the graphical overviews, we identified the relationships between the concepts in such a way that they were in line with the instructional material. Thus, when the explanation of one topic included another topic, there was a relation. Then, we arranged the concepts in the graphical overview, so that there were no crossing relations.

5.3 Design

We used a crossover experimental design, in which each participant worked with both tools. To compensate for carry-over effects, the order of the tools and domains was counterbalanced. The resulting four combinations are presented in Table 8.

Table 8
Overview of groups in study design.

	First Trial		Second Trial	
Group	Tool	Domain	Tool	Domain
1	CG	MCS	LG	CR
2	CG	CR	LG	MCS
3	LG	MCS	CG	CR
4	LG	CR	CG	MCS

MCS = Measures of Center and Spread
CR = Correlation and Regression

The independent variable was the type of tool provided and the dependent variables were factual knowledge, conceptual knowledge, structural knowledge, task load, time allocation, and motivation. The overall time participants worked with the tools was controlled, but participants were free to allocate their time between different parts of the tool. We did not use a pre-test because this might interfere with the effects of the planning tools used in this study. Furthermore, because the data was analyzed within subjects, we did not need to control for individual differences, such as prior knowledge.

Participants

Eighty-three behavioral science students participated in the study, 18 males and 65 females. Their average age was 19.49 years (*SD* = 1.63). They received credits for participating. The subject matter used in the study (introductory statistics) was relevant for the participants, because the subject is addressed in their first year. Participants had not started on their introductory statistics course and their prior knowledge was expected to be low. Participants were randomly assigned to one of the four groups described in the 'design' section above.

Measurements

Knowledge

Three types of knowledge were measured: factual, conceptual, and structural knowledge. Factual knowledge addressed isolated statements about the learning domain. Factual knowledge did not require understanding of the material. An example of a factual knowledge test item was: 'There are four quartiles'. Factual knowledge was measured with 16 items for each domain. Participant could indicate whether a given factual statement was either correct or not. The score was the number of correct items and ranged from 0 to 16.

Conceptual knowledge addressed the connected and integrated knowledge about the learning domain. To measure conceptual knowledge, items from the fourth version of the Comprehensive Assessment of Outcomes in Statistics (CAOS) and from the Artist database were used (delMas, Garfield, Ooms, & Chance, 2007). Those items were developed to measure how well students understand important basic statistical concepts. The CAOS items have shown adequate reliability, validity, and discriminative power. For each learning domain 26 multiple choice items were used. The score for the participants was the number of correct items and could range from 0 to 26.

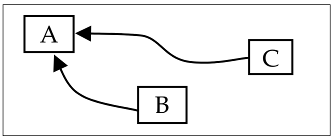


Figure 23. Example of Structural Knowledge in Graphical Overview.

Structural knowledge was defined as knowledge about the relations shown in the graphical overview. Structural knowledge was addressed with closed items that addressed the structure of the graphical overview. For every item, participants had to indicate whether there was a relation between two concepts. In the example shown in Figure 23, there is a relation between B and A (and between A and B), and between C and A (and between A and C) but not between B and C. There were 32 structural knowledge items per topic. Again, the score was the number of correct items and could range from 0 to 32.

Judgment of Learning

JOL was measured by asking participants to indicate from which tool they learned most. The following two questions were used 'From which way of working did you learn most from the domain contents?' and 'From which way of working did you learn most about the structure shown in the graphical overview?' For both questions, participants could select: manually, automatic, or no-difference.

Task load

To measure the overall task load, an adapted version of NASA's Task Load Index (TLX) was administered twice. Participants were asked to rate the whole learning process, including both planning and learning. The TLX was developed by Hart and Staveland (1988) and combines characteristics of the task, and of the conditions under which it was taken into one score. The original version uses 6 scales and 15 pair wise comparisons between the scales. In this experiment, the scale 'physical demand' was removed, because physical demands were not relevant for this study. Thus, the TLX was used with 5 remaining scales (mental demand, temporal demand, performance, effort, and frustration level) and 10 pair wise comparisons between the scales.

Time Allocation

The tools used in the study stored how long participants worked with different parts of the tool. To analyze the behavior of the participants, three distinct processes were identified: planning time, reading time, and graphical overview time. The planning time, was the time participants worked on creating the plan. When the participants had finished the plan, they started traversing it. Participants could either read the instructional material (reading time) or study the graphical overview (graphical overview time).

Self-Reporting Measures

To measure specific aspects of the learning process, participants received a number of statements and indicated whether they agreed with a given statement on a 5 point Likert scale. The following concepts were each tested with three questions: clarity of the learning goal, the activation of prior knowledge, difficulty of creating plans, and whether the use of software made the planning easier. For example, to measure prior knowledge activation participants received the following questions: 'my prior knowledge was activated when working with the LG-tool', 'my prior knowledge was activated when working with the CG-tool', and 'my prior knowledge was better activated when working with the LG-tool, compared to the CG-tool'. Furthermore, participants received a number of single statements and were asked whether they agreed with the statement on a 5 point Likert scale. These (translated) statements are listed in Table 9.

Table 9

Statements used in the self-reporting measurement.

#	Statement
1	I had more time for studying when I worked with the CG-tool.
2	If you create a learning plan, you already learn from planning.
3	When I created the learning plan myself, I had more control over the learning process, compared to when the computer created it.
4	I rather select the learning goal myself, and not have it selected by the computer.
5	When I study, I prefer to have control over the learning process, compared to giving the computer control.
6	By actively creating a planning, it is easier to understand information, compared to when the computer created the plan.
7	It would be useful to have a planning tool for difficult topics.
8	It would be useful to have a tool with a graphical overview for difficult topics.
9	Due to planning, I had too little time left for learning.

Motivation

Motivation was measured with a translated version of the scale developed by (Zumbach, 2009). This scale is based on the concept of interest and the state experience of flow. The statements used were 1) The software and the subject are interesting. 2) I would like to continue working with the software. 3) The software and the subject are boring. 4) It is fun using the software. 5) The software and the subject are fascinating. Participants indicated how well they agreed with each statement on a five point Likert scale. To determine the motivation, the inverted item was reversed and motivation was defined as the sum of five resulting scores. Motivation could range from 5 to 25.

Tool Preferences

To measure tool preferences, participants indicated which tool they would prefer in two hypothetical situations. One item was: 'If you would have to learn a topic yourself, which tool would you prefer?' The other was: 'If you were to create a learning plan for someone else, which tool would you prefer?' For both items, participants could select: the LG-tool, the CG-tool, or no-preference.

Procedure

Participants were tested in the computer laboratory in groups of approximately 15 persons. A session took 105 minutes to complete. The sessions started with a plenary explanation and demonstration of the tools. Participants were explained that they had to plan and perform learning and that they had to complete tests afterwards. The demonstration of the tools was performed with a projector and a big screen. Then, participants individually completed a tutorial and a practice session with the practice domain, that dealt with dealing with tool. In the tutorial, participants learned to work with the tools and applied that knowledge in the practice session. In the practice session, participants created a plan, traversed the learning contents, and completed knowledge tests about the practice domain.

After the introduction, participants worked on the first trial. Although all participants worked with both tools, the order of the tools and the domain depended on the group they were assigned to. Depending on their group, participants received one tool with one of the two topics. After the plan, either constructed by the participant or by the computer, was approved, the tools arranged the learning material according to the plan. Participants then traversed the learning material. Once they had started traversing the learning material, they could not go back to the planning phase. After 18 minutes, the TLX was administered, followed by the motivation questionnaire. Then the conceptual knowledge test, structural knowledge test, and factual knowledge test were administered respectively. The completion of the tests took 20 minutes. When all tests were completed, participants started on the second trial using the other tool and the other topic. This again took 18 minutes, followed by the same test types as in the first run. After all the tests were completed, participants completed the forms with the self-reporting measurements about the learning processes and their preferences.

5.4 Results

Knowledge

In the experiment, one knowledge test addressed 'correlation and regression' and one 'measures of spread'. To compare these scores the results were normalized and the resulting *z*-scores were used in the analyses. To find effects, we used a repeated measure multivariate analysis of variance with the order of the tools and the order of the domains as between-subjects factors.

Using Pillai's trace, there was no significant main effect of the tool on the knowledge tests' scores, $V = 0.04$, $F(3, 76) = 0.96$, $p > 0.05$, and no interaction effect between the order of the domains and the used tool, $F(3, 76) = 0.91$, $p > 0.05$. There was an interaction effect between the type of tool used and the order in which the tools were used, $V = 0.12$, $F(3, 76) = 3.36$, $p < 0.05$. Univariate analysis of this interaction effect showed that the effect was significant for structural knowledge, $F(1, 82) = 8.87$, $p < 0.05$, but not for factual knowledge, $F(1, 82) = 1.56$, $p > 0.05$, nor for conceptual knowledge, $F(1, 82) = 0.59$, $p > 0.05$. The interaction effect showed that participants gained more structural knowledge working with the first tool they used, compared to the second tool, independent of which tool that was.

Table 10

Knowledge test scores.

	LG-Tool		CG-Tool	
	Score *M (SD)*	*z* score *M (SD)*	Score *M (SD)*	*z* score *M (SD)*
Factual Knowledge	10.59 (2.20)	-.03 (.94)	10.69 (2.54)	.02 (1.06)
Conceptual Knowledge	12.06 (3.72)	-.01 (.97)	12.10 (3.74)	.01 (1.03)
Structural Knowledge	19.12 (3.39)	.04 (.97)	18.82 (3.61)	-.05 (1.03)

Further analysis showed that participants who explicitly reported that they had gained more structural knowledge while working with the LG-tool, did not score higher on the structural knowledge test with that tool, compared to the CG-tool, $F(1,58) = 2.72$, $p > 0.05$. Likewise, participants who thought that they had learned more conceptual knowledge with the LG tool actually did not score higher on the conceptual knowledge test, $F(1, 55) = 0.54$, $p > 0.05$. Remarkably, they had a higher score on the structural knowledge test, $F(1, 55) = 4.72$, $p < 0.05$.

Judgement of Learning

To measure JOL, participants were asked to indicate from which tool they learned most for domain knowledge and for structural knowledge. Table 11 shows how many participants selected the different options. McNemar's test indicated no significant differences between the participants' answers for the learning domain contents and the structural knowledge, McNemar's χ^2 (1, $N = 83$) = .39, $p > .05$. For both types of knowledge, most participants thought that they had gained more structural and domain knowledge while working with LG-tool.

Table 11

JOL for domain and structural knowledge.

		Learning domain knowledge		
		LG-tool	CG-tool	Total
Structural knowledge	LG-tool	46 (55.4%)	13 (15.7%)	59 (71.1%)
	CG-tool	10 (12.0%)	14 (16.9%)	24 (28.9%)
	Total	56 (67.5%)	27 (32.5%)	83 (100%)

Note. Learning domain knowledge is factual and conceptual knowledge.

Task Load

There were no differences between the task load for both tools, $F(3, 79) = 1.40$, $p > 0.05$, and there were no interaction effects between the tool order, $F(3, 79) = 2.65$, $p > 0.05$, and the domain order, $F(3, 79) = 1.25$, $p > 0.05$. Further analysis revealed that with the LG-tool, there was a positive relation between the time participants needed to create the plan and the perceived task load, $r = .22$, $p < 0.05$. Thus, the longer it took to create an approved plan, the higher the self-reported task load.

Time Allocation

The tool influenced the times that participants used different parts of the learning environment. The mean times are shown in Table 12 below. Separate univariate ANOVAs showed that participants spent more time on planning with the LG-tool, $F(1, 82) = 116.34$, $p < 0.05$, and spent more time on reading the learning material with the CG-tool, $F(1, 82) = 75.03$, $p < 0.05$. Furthermore, with the LG-tool participants spent less time on studying the graphical overview after the planning phase, $F(1, 82) = 19.10$, $p < 0.05$. Participants reported that they had more time for studying the learning material when they used the CG-tool, $CI_{.95} = [3.25, 4.24]$§ and that due to planning activities, they had too little time to study the learning material, $CI_{.95} = [3.02, 3.55]$.

Table 12

Average times working with different parts of the tools.

	LG-tool (s) *M (SD)*	CG-tool (s) *M (SD)*
Planning *	334.86 (223.30)	53.12 (96.72)
Studying Graphical Overview *	141.71 (136.86)	219.74 (172.61)
Reading Learning Material *	636.80 (219.42)	840.56 (170.33)

* comparing times for the LG-tool and CG-tool at $\alpha = 0.05$

Self-Reporting Measures

Based on the self-report questions, participants indicated that the goal of learning was clearer when they used the LG-tool ($M = 3,67$, $SD = 0.95$) than when they used the CG-tool

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§ Results from the self-reporting items were interpreted as interval data. If the interpretation of the scale is not explicitly described, the scales range from 1 = *totally disagree*, through 3 = *neutral*, to 5 = *totally agree*. For these items, we present a ninety-five percent confidence interval for the mean, $CI_{.95}$ = [lower bound, upper bound]. We interpreted that participants disagreed with the statement, if the upper bound of the confidence interval was lower than 3, and that they agreed with the statement if the lower bound was higher than 3.

($M = 2.86$, $SD = 0.99$), $t(82) = 4.73$, $p < 0.05$. Furthermore, they agreed with the statement that the goal of learning was clearer working when working with the LG-tool, $CI_{.95} = [3.22, 3.92]$.

Participants also reported that their prior knowledge was better activated with the LG-tool ($M = 3.19$, $SD = 0.92$) than with the CG-tool ($M = 2.60$, $SD = 1.07$), $t(82) = 3.69$, $p < 0.05$. Furthermore, they agreed with the statement that their prior knowledge was better activated with the LG-tool, $CI_{.95} = [3.25, 4.05]$.

Participants also agreed with the statement that it was easier to understand new knowledge when they used the LG-tool, compared to using the CG-tool, $CI_{.95} = [3.21, 4.53]$. They also agreed with the statement that they gained knowledge from the active planning process itself, $CI_{.95} = [3.21, 5.02]$.

Motivation

We found an internal consistency of the motivation scale of Cronbach's alpha = 0.87. There was no difference in motivation between the tools, $F(1, 82) = .02$, $p > 0.05$, but there was an interaction between the order of the conditions, $F(1, 82) = 18.29$, $p < 0.05$. This indicated that participants were more motivated when working with the first tool used, compared to the second tool, independent of which tool that was. Participants preferred to have control over the learning process, compared to giving the computer control, $CI_{.95} = [3.24, 4.25]$ and they thought they had more control over learning with the LG-tool then with the CG-tool, $CI_{.95} = [3.24, 3.80]$. They also agreed with statement 'I'd rather determine the learning goal myself, than having a computer do that for me.', $t(82) = 4.71$, $p < 0.05$. $CI_{95} = [3.20, 4.19]$.

Tool Preferences

Most participants preferred to use the LG-tool, when the plan was for themselves and the CG-tool, when the plan was for someone else. Table 13 shows their responses. McNemar-Bowker's test indicated a significant difference between the answers for the two hypothetical situations, McNemar-Bowker $\chi^2(3, N = 83) = 24.31$, $p < .05$. To measure the difference between the answers, we scored the selection for the LG-tool as 1, the selection for the CG-tool as -1, and the selection for no preference as 0. Using a paired samples t-test there is a significant difference between the preference participants had for their own learning ($M = 0.25$, $SD = 0.88$) and for the learning of others ($M = -0.43$, $SD = 0.87$), $t(82) = 5.3$, $p < 0.05$. Moreover, most participants preferred to use the LG-tool, when the plan was for themselves and the CG-tool, when the plan was for someone else.

Table 13

Tool preferences when the plan is for participants themselves or for someone else.

		Plan for yourself			Total
		LG-tool	CG-tool	No preference	
Plan for someone else	LG-tool	13 (15.7%)	5 (6.0%)	3 (3.6%)	21 (25.3%)
	CG-tool	29 (34.9%)	18 (21.7%)	10 (12.0%)	57 (58.7%)
	No preference	3 (3.6%)	1 (1.2%)	1 (1.2%)	5 (6.0%)
	Total	45 (54.2%)	24 (28.9%)	14 (16.9%)	83 (100%)

Participants thought that the creation of a plan was easier with ($M = 2.51$, $SD = 1.08$) then without the software ($M = 3.18$, $SD = .84$, 1=very easy 5=very difficult), $t(82) = 4.70$, $p < 0.05$. Furthermore, participants agreed with the statement that it was easier to create the plan with the software then without it, $CI_{.95} = [3.25, 4.48]$.

Participants thought it was useful to have graphical overviews for difficult learning domains, $CI_{.95} = [3.22, 4.57]$ and to have planning support tools, $CI_{.95} = [3.22, 4.52]$.

5.5 *Conclusion and Discussion*

In this study, we examined whether active planning one's own learning route through a learning domain was beneficial for the learning process and outcomes. To that goal, we set up an experiment in which we compared two tools. With the tool in the experimental condition, the LG-tool, learners generated learning plans manually. With the tool in the control condition, the CG-tool, the computer generated the plans automatically. The main result of this study was that, although most participants thought that with the LG-tool it was easier to process the learning material, that prior knowledge was better activated and that they had learned more, knowledge tests showed no significant differences between the tools. Even participants who explicitly indicated that they had gained more knowledge of a specific type with the LG-tool did not score higher on the corresponding tests.

In a previous study, we examined the effects of planning on knowledge and task load (Bonestroo & De Jong, 2009). In that study, knowledge tests were administered after planning, but before the actual learning phase had started. Results from that study demonstrated that active planning led to more structural knowledge compared to automated planning and there were no differences for factual knowledge. In the current study, planning was integrated in the whole learning process and we expected that learning would be better when learners started with a better understanding of the learning domain structure. However, results did not support that hypothesis. In the following, these results are discussed in the context of Winne and Hadwin's SRL model (1998).

Although the tools did not influence learning outcomes, they did influence performed operations. We found that the tools influenced the distribution of time over the SRL phases. Participants using the LG-tool spent more time on planning activities (second phase) and participants using the CG-tool spent more time on reading learning material (third phase). In line with the log files analyses, participants reported that they had more time to read the study material while working with the CG-tool. They also indicated that they had too little time to study the learning material with the LG-tool and this might explain the results of this study. In our study, the total time was controlled, so the longer participants spent on planning, the less time they had left for learning. Log file analysis also revealed that with the CG-tool participants used the graphical overview during the later stages of the learning process. It appeared that participants used the graphical overview to compensate for their lack of structural knowledge.

In this study, participants were not able to correctly predict with which tool they had learned most. After working with both tools, they could not accurately perform judgment of learning (JOL). To perform JOL, learners require an understanding of the learning goal and the learning plans. According to self-report measurements, participants had a clearer view of the learning goal with the LG-tool. The difficulties learners face when performing JOL lead to an unsolved dilemma in the design of CBLEs. Most learning environments allow learners to select their own tools. Based on our findings, we should question whether learners are able to determine which tools work best for them. In our study, participants had actually used both tools, before they predicted which tool was the best. Moreover, the tools used a simple form a planning. If a planning tool also includes decisions on what learning activities to perform, and if learners should choose their tool before actually using them, it might be even more difficult to make correct instructional decisions.

In our previous study (Bonestroo & De Jong, 2009), we found an increased task load for the active planning and we expected a similar pattern for this study. However, in the current study, we found no differences in task load for the whole learning process, suggesting that there were no differences in overall working memory load. The fact that task load was similar could indicate that planning does not heavily contribute to the total task load of the whole process, or that studying learning material, without knowing the overall structure, increases frustration and task load. In the light of Moos and Azevedo (2008c) theoretical explanations, the form of planning that we used in this experiment did not overload the cognitive systems of the participants.

Increased learner control in CBLEs is associated with increased motivation and interest (Cordova & Lepper, 1996; Scheiter & Gerjets, 2007). Although participants indicated that they preferred to have control over learning and that they thought they had more control over the learning process with the LG-tool, they did not score higher on the corresponding motivation measurement. Accordingly, motivation was not a good predictor for tool preference. When participants were asked which tool they would prefer to use, they preferred the LG-tool when the plan was for themselves, and they had no preference when the plan was for someone else. Eccles and Wigfield's expectancy value theory (2002) seems to provide a better explanation of the tool-preference. When participants would use the tool for their own learning, they preferred the tool in which they thought they had learned most.

A limitation of this study was that the learning sessions took 18 minutes. If a planning tool is used in an authentic educational setting, it is not uncommon for planning to cover several hours, weeks or even months. As prior research shows that there are different types of planning and that these types have different effects, we should take care when we want to generalize the findings of the current study to larger learning sessions. In the current study, we used a graphical overview that fitted on the computer screen. Thus, participants did not have to scroll or zoom to watch the overview. Larger overviews might be more difficult and more demanding to navigate. Time was controlled in this experiment. In an educational setting, however, this is not always the case. In the classroom, the total amount of time is fixed, but for studying and doing homework, students are often free to determine whether and how long they learn. It would be interesting to investigate the behavior of participants, such as the total study time, when they are free to use the tools and can also decide how long they use the tools.

Based on these findings, there appears to be a planning illusion. Although planning intuitively plays an important role in the learning process, literature suggest that it is an essential part of the process, and participants indicated that they learned more from active planning, empirical results did not support this idea and showed a discrepancy between participants' judgment of learning and their actual learning outcomes. As our previous study (Bonestroo & De Jong, in press) demonstrated that active planning led to more structural knowledge directly after the planning process, it remains the question how this effect can be utilized to improve the whole learning process.

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Chapter 6

General Discussion and Conclusion

Abstract

In this chapter, we summarize the findings from the three studies that were performed during this project. We discuss the implications of our findings for the fields of self-directed learning and technology-enhanced learning. Furthermore, the limitations of the studies are addressed and we give recommendations for future research. In the concluding section, the research questions, stated in the introductory chapter, are answered and our position on planning in computer-based learning environments is formulated.

6.1 Introduction

In this work, we examined whether actively planning one's route through a learning domain was beneficial for the learning process. Planning takes place in the preparatory phase of the self-regulated learning (SRL) process, in which learning goals are established and plans of how to reach those goals are developed (Puustinen & Pulkkinnen, 2001). Because planning is performed as one of the first activities in the process, it has the potential to influence subsequent learning processes and eventual learning outcomes of that processes. According to SRL literature, planning is an essential activity and several authors have pointed out its potential to improve SRL (e.g., Azevedo, Guthrie, & Seibert, 2004; Boekaerts, Pintrich, & Zeidner, 2005; Hattie, 2009; Zimmerman & Schunk, 2001). During planning, learners actively process high-level structural information about the learning domain. Accordingly, we expected that active planning would result in a better understanding of the overall structure of the learning domain. And because such understanding of the structure of the learning domain can be used for chunking information and can help to sort and interpret new information, we hypothesized that active planning would act as a scaffold for the whole learning process and result in improved learning outcomes.

During planning, learners make instructional decisions about their own learning process; they have to decide how they are going to tackle a certain learning problem. Research shows that learners do not always make good instructional decisions when given freedom in the learning process (e.g., Bell & Kozlowski, 2002). Correspondingly, self-regulative activities, such as planning, can be difficult to perform correctly without external guidance (Azevedo, et al., 2004). Computer-based learning environments (CBLEs) can automatically provide such guidance to learners. Such environments can even perform complex tasks such as planning learning. Learning plans can be created tailored to the needs of the individual learner. Because automating such tasks from the learning process influences learners' cognitive processes, it could also influence learning outcomes. However, there is little empirical evidence on the effects of active planning on learning yet. Claims about positive effects of planning on learning are not fully backed up by empirical research and our review of the literature revealed no experimental studies in which only the planning process was varied. In this work, we examined whether planning of learning can better be performed by the computer or by the learner. Based on the current literature on SRL, we expected that active (manual) planning would lead to better knowledge about the learning domain, because learners would be more actively involved in the learning process and because they would address information about the structure of the learning domain in the learning process.

To test these assumptions, we set up three experimental studies in which we examined software tools that aimed to support planning. All used tools contained graphical overviews that visualized the learning domain's structure. Graphical overviews explicitly show the interconnected structure of learning material, and research shows that graphical overviews can help learners to grasp this structure more easily (e.g., Chen & Rada, 1996; Nesbit & Adesope, 2006). Although graphical overviews are generally considered beneficial for learning, the non-linear characteristics of graphical overviews can make them complex to navigate and, in turn, this could negatively influence learning (Scheiter & Gerjets, 2007). In our first study, we examined an intervention to implicitly guide the navigation in graphical overviews. The research question addressed in that study was:

> *Does the visualization of prerequisites in graphical overviews guide navigation through the learning domain and does it lead to better task performance and more knowledge?*

In that study, we experimentally compared two software tools. Both tools contained a graphical overview representing the learning domain, but in one tool the overview also visualized prerequisite relationships. Prerequisites indicate that some topics should be learned before other topics can be learned. The goal of this visualization was to let learners think about the route they took through the domain and to guide them through the domain in such a way that for each topic, they would first address the prerequisite topics and then the advanced topics. Thus, learners were expected to take a more domain related route when they were provided with the prerequisite visualization. We expected that this would lead to better connected knowledge and understanding of the domain and also to better task performance. We compared the effects of the tools on participants' browsing behaviour, task performance, and their knowledge. Based on the findings from the first study, an explicit planning component was added to the software to emphasize the planning of the learning material. The research question addressed in both the second and third study was:

> *Do learners learn more when they are actively involved in the planning process, compared to when they are provided with automatically generated plans?*

In both studies, we examined whether actively planning one's learning was beneficial for learning. In both studies, we again compared two tools. In the tool in the experimental condition, learners manually generated their own plans (the LG-tool), while in the tool in the control condition, the learning plans were generated by the computer (the CG-tool). We measured participants' quality of created plans, navigation behaviour, task load, and acquired knowledge. In the second study, knowledge was measured directly after the planning phase, but before the actual learning had started. In the third study, knowledge was measured after the whole learning process. Figure 24 graphically depicts when the measurements were performed for the second and third study.

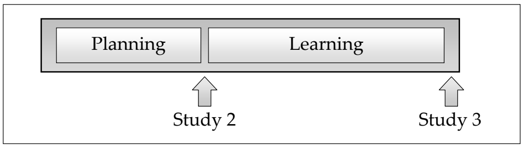

Figure 24. Measuring moments for studies 2 and 3.

In the second study, participants worked with the structural information from the graphical overview. Moreover, they had access to limited learning material consisting of the definitions of the concepts represented in the graphical overview. In the third study, however, participants received comprehensive learning material about the topics after they had completed the planning phase. The measurements in the third study were performed after the participants had processed the learning material.

6.2 *Summary of Empirical Studies*

In this section, the three empirical studies are summarized in chronological order. For every study, we describe the research method and findings. The section that follows this summary provides an interpretation of these findings in the light of the current understanding of SRL and TEL.

Study 1: Enhancing Graphical Overviews

In our first study, described in Chapter 3, we developed and tested the effects of an instructional cue that visualized prerequisite relationships in graphical overviews. We wanted to know whether those visualizations guided navigation through the learning domain and whether it led to better task performance and more knowledge. Two tools were compared in this study. The tool in the control condition had a standard graphical overview and contained learning material for each topic that was visualized in the graphical overview. The tool in the experimental condition was identical to the one in the control condition, except that the graphical overview also visualized prerequisite relationships between topics. A prerequisite relation was displayed as an arrow between two topics. The direction of the arrow indicated the order in which the topics should be addressed. In the study, participants were asked to perform tasks that involved solving statistical problems. The tasks were designed in such a way that participants needed to consult information available in the tool. To access that information, participants could select a topic in the graphical overview and could then select which resource they wanted to see.

In the study, forty-two participants worked with one of the two software tools. Participants received well-structured and ill-structured tasks. Well-structured tasks contained hints or directions about the correct solution. An example of a well-structured task is: "Use regression analysis to determine the effects of *a* on *b*." In this example, the appropriate analysis is already stated in the question and participants could search the graphical overview in a goal directed way. Ill-structured tasks, on the other hand, did not contain such information such as the name of the analysis. In such cases, the tasks provided no hints on the solution and participants had to identify a correct approach themselves. Thus, they had to use a more exploratory approach in the graphical overview. An example of an ill-structured task is: "Is there is significant difference between *a* and *b*?" We measured the effects of the prerequisite visualization on navigational behaviour, task performance, and learning outcomes. Moreover, the tools recorded the participants' navigational behaviour in log files. Task performance on the statistical problems was determined based on the quality of the solutions for the given tasks. Participants' knowledge was measured with a multiple choice knowledge test, containing factual and conceptual items. Factual items addressed knowledge about one individual topic, whereas conceptual items addressed multiple topics and required insight in the relationship between those topics. Accordingly, conceptual items aimed to measure what Schau and Mattern (1997) called "connected understanding". Based on the literature, we expected that learners would follow the instructional cues provided by the prerequisite visualization and that this would lead to better knowledge about the learning domain and to better performance on the tasks.

Results from the study demonstrate that navigational behaviour in the graphical overview was indeed influenced by the visualization of prerequisite relationships, but only for well-structured tasks. For ill-structured tasks, participants did not follow the provided cues. Although the visualization did influence browsing behaviour, no effects were found for task performance or for knowledge. The visualization of prerequisites influenced neither factual nor conceptual knowledge. One important observation from the first study was that participants did not use the information in the graphical overview as expected. Participants often read advanced topics without giving sufficient attention to their prerequisite topics. Thus, they did not approach the learning process as the accumulation of information from several sources.

Study 2: Planning and Structural Knowledge

To prevent learners from directly addressing difficult topics without addressing the prerequisite topics, we added an explicit planning component to our tool. With this component, learners planned their learning by creating a sequence of topics based on the information in the graphical overview. The learning material was then ordered according to the plan and presented to the learners. As described in Chapters 1 and 2, the use of computational models of learning domains and learners allows automating planning processes. However, based on the literature, we wanted to know whether such technological advances would actually benefit learning. In the second study, described in Chapter 4, we examined the effects of two planning tools on navigational behaviour, task load, acquired knowledge, the quality of created plans, and preferences for the tools. In the tool used in the experimental condition, learning plans were actively generated by the learners themselves (the LG-tool). In the tool in the control condition, they received an adaptable plan that was automatically generated by the computer (the CG-tool).

In the second study, sixty-five participants each worked with both versions of our tool. Participants only received well-structured tasks in which they were asked to create and inspect learning plans to achieve a given learning goal. We expected that when participants would actively create the learning plan themselves, they would have more knowledge about the structure of the learning domain, but less knowledge about the factual contents. Results of the second study demonstrated that participants indeed had more knowledge about the structure of the learning domain when they had worked with the LG-tool. Moreover, actively creating plans did not impede the acquisition of factual knowledge; there was no significant difference in factual knowledge after working with the LG-tool compared to working with the CG-tool. However, participants reported a higher task load when they constructed the plans themselves and the quality of learner-created plans was lower than that of computer-generated plans. To measure the preferences of participants, we asked them which tool they would prefer to use in two hypothetical situations. Participants did not have an apparent preference for either one of the tools if they were to create a plan for someone else. However, if participants were to use the plan for their own learning, the majority preferred working with the LG-tool.

Study 3: Does Planning Support Learning?

In the third study, described in Chapter 5, we examined whether the effects of actively planning found in the second study would also have an influence on the whole learning process. To that goal, the planning tool was integrated in a CBLE with accompanying learning material. We measured the effects of the tools on the following variables: factual knowledge, conceptual knowledge, structural knowledge, task load, learning processes, motivation, and tool preferences. In the third study, knowledge was measured after the whole learning process; after both planning and performing the actual learning activities. In the study, participants were asked to plan their learning to reach a given learning goal. Then, they received the learning material according to the order in their plan. Based on the findings from the second study, we expected that participants would have better knowledge of the learning domain structure when they created their own plan compared to when they received an automatically generated plan. Eighty-three participants worked with both tools over a series of different topics in introductory statistics and data analysis. Because the findings of the second study suggested inconsistencies between the perceived and the actual factual knowledge, we explicitly measured perceptions of knowledge in the third study.

Results from our third study showed that the tools influenced the learning process and that there was a pronounced inconsistency between learning perceptions and outcomes. Participants indicated that they had performed more learning activities when they used the LG-tool. Correspondingly, the majority of participants thought they had learned most when they had actively created their own plans. Interestingly, the knowledge tests showed no significant differences; there were no differences between the tools for either factual, conceptual, or structural knowledge. Participants reported that they had more learner control when they used the LG-tool, but there was no increase of motivation when participants used that tool. Nevertheless, learners preferred the LG-tool when they were to use the learning plan themselves. When the plan was for someone else, they had no apparent preference.

6.3 General Discussion

Planning is considered an essential activity and several authors have suggested its potential to positively influence learning. The tools used in our studies influenced how participants approached the learning material. In line with the literature, participants in our study thought that their learning was better when they had actively planned their learning, compared to when they received an automatically generated plan. However, this perception was only reflected in the intermediate learning outcomes and not in the results on the knowledge tests administered after the whole learning process. Participants who actively planned their learning had gained more structural knowledge directly after planning. However, this improved initial structural knowledge was not visible after the whole learning session and we found no evidence that it was beneficial for the acquisition of conceptual knowledge. Accordingly, there appears to be a “planning illusion”. Although literature suggests that planning leads to better learning outcomes, we did not find evidence for this. As SRL is becoming more popular, we think it is important to understand the consequences of planning on learning.

Effects of Planning on Learning

The rationale for letting participants plan their own learning is the assumption that planning is beneficial for learning. Planning stimulates active processing of high-level structural information. Knowledge of this structural information at the start of the learning process is assumed to support the subsequent phases in SRL. In our second study, we measured participants’ knowledge directly after the planning phase. Two tools were compared in that study. In one tool, learners actively generated their own learning plan (the LG-tool) and in the other tool, participants received a plan that was automatically generated by the computer (the CG-tool). We found that participants had better structural knowledge when they had worked with the LG-tool compared to when they had worked with the CG-tool. A plausible explanation of these findings is that learners were more actively involved in the learning process and that they better processed the information in the graphical overview. These results are consistent with the theories of active learning that posit that people learn by doing (Stull & Mayer, 2007). According to the description provided by Mayer (2004), the activities that participants in our studies performed during planning could be classified as cognitive activities and, accordingly, such activities are expected to support the learning process. Based on the suggestions provided by Jonassen (1993), we expected that there would be a trade-off between structural and factual knowledge. Thus, when participants would focus more on the structural knowledge, we expected that they would acquire less factual knowledge. However, our results showed no differences for factual knowledge directly after planning. Based on our findings in the second study, we concluded that active planning of a brief learning session led to a better knowledge of the learning domain’s structure directly after the planning and does not hamper factual learning. In this light, it would be desirable to include active planning components in CBLEs. To test whether these effects influenced the whole learning process, we set up the third study. In that study, participants first created a plan and than accessed the learning material according to that plan. Results from our third study showed no significant differences in the outcomes of the knowledge tests administered after the whole learning process. Thus, whereas the structural knowledge was higher directly after planning, after the whole learning process there were no significant differences in knowledge anymore. When participants received an automatically generated plan, they somehow compensated for the initial lack of structural knowledge in the latter phase of the learning process. The log files revealed one possible explanation of this effect. With the CG-tool, participants took considerably more time to examine graphical overviews in the latter phase of the learning process. Thus, when learners did not create their own planning at the start of the session, they spent more time studying the graphical overview in the latter phases of the learning process. Another explanation is that participants obviously required considerably less time for planning with the CG-tool and, therefore, they had more time for the actual learning phase. The task load for both tools was also measured in both the second and the third study. We expected that task load would always be higher when participants actively created their plans. The results of the second study confirmed this expectation. However, in the third study, there was no significant difference in the task load for the CG-tool and the LG-tool. The fact that there was no difference in the perceived task load for the whole learning process could indicate that planning does not heavily contribute to the total task load or that studying learning material, with less knowledge of the overall structure, increases task load and possibly increases active processing of the learning material. Van Patten, Chao, and Reighluth (1986) described a remarkable study in which participants in the worst instructional condition tried so hard to make sense of the learning environment, that they outperformed participants in the other, better, conditions. Altogether, with regard to task load, we conclude that active planning of a brief learning session does not influence the overall perceived task load. Moreover, it does lead to improved structural knowledge directly after planning, but it does not lead to better learning outcomes after the whole learning process.

Learner Control and Motivation

In the third study, participants indicated that they experienced more learner control with the LG-tool and that they also preferred that tool if they were to plan their own learning process. Although increased learner control is generally associated with increased learners' motivation and interest (e.g., Scheiter & Gerjets, 2007), others have argued that empirical evidence on the topic is mixed and confusing, and that there is a growing controversy over the advantages and disadvantages of unrestricted choices in learning situations (Katz & Assor, 2007). Although participants in our study clearly perceived that they had more learner control with the LG-tool, the actual learner control for both tools was rather similar. With the LG-tool, participants were free to edit their plans the way they wanted to, however, the prerequisite relationships constrained the number of correct plans considerably. In the end, all participants had the same concepts in their plans and only the order of the concepts could be different. However, when learners worked with the CG-tool, they were also free to edit the plan that was provided by the computer. Accordingly, the participants perceived more learner control with the LG-tool, while in fact the amount of learner control was rather similar. In our third study, we found a difference in perceived learner control, but no difference in motivation. Nonetheless, participants preferred to use the LG-tool if they were to use it for their own learning. In her literature review on the effectiveness of learner control in computer-assisted instruction, Lunts (2002) distinguished several types of learner control: content control, sequence control, and advisory control. With regard to sequence control she concluded that "better post-test scores or attitudes toward CAI associate with modest amounts of sequence control in CAI" (p. 64). Modest amount of sequence control entails that learners have control over the learning sequence, but that they receive support in the process. In line with her conclusion, we found that participants had a more positive attitude towards the LG-tool. However, although participants in our study had "modest amount of sequence control" they did not achieve better post-tests scores with that tool. Our findings are similar to those of Flowerday and Schraw (2003), who hypothesized that choice in the learning process would have a positive effect on learners' attitude and effort. Based on their results, the authors concluded that when participants had the opportunity to choose their activities, they perceived a greater sense of control and this had a positive effect on measures of affective engagement. Flowerday and Schraw also measured the cognitive engagement as the performance on a cognitive task. They expected that the provision of choice would have a positive effect on cognitive engagement. However, in their experiment, they did not find evidence that supported their hypothesis. Although participants in our studies reported more cognitive learning processes when they worked with the LG-tool, we also did not find significant differences on the learning outcomes.

Instructional Cues in Graphical Overviews

We set out this research project with the idea that learners' self-regulated learning can be supported with information stored within CBLEs, such as domain models. According to the literature, graphical overviews are ideal tools for the representation of the structure of learning domains. However, graphical overviews are also known to be difficult to navigate and this can lead to problems such as disorientation and, in turn, this can impede learning. The intervention in our first study was based on the conception of prerequisites, and aimed to support navigation in graphical overviews. Prerequisites form the foundation of many influential learning theories, such as the theories of Ausubel (Ausubel, et al., 1978; Novak, 2002), Gagné (Gagné, 1973, 2005), and Reighluth (English & Reighluth, 1996). Our tool in the experimental condition, visualized prerequisite relationships in graphical overviews to indicate an appropriate route through the learning domain. We found that the visualization of prerequisites guided the navigational behaviour for well-structured tasks, but not for ill-structured tasks. Participants browsed more relevant topics (both main topics and prerequisite topics) when they worked on well-structured tasks while prerequisite relationships were visualized. These findings are in line with research on navigational behaviour in graphical overviews that demonstrates that navigational behaviour can be guided by the structure of the graphical overviews and by navigational cues or hints (de Jong & van der Hulst, 2002; McDonald & Stevenson, 1998; Vekiri, 2002). However, because we found that navigational cues in graphical overviews only guided navigation when participants were performing well-structured tasks and not when they were performing ill-structured tasks, we concluded that the effectiveness of our intervention was mediated by characteristics of the learning task. A plausible explanation of our findings is that solving ill-structured problems is an inherently complex task. The use of graphical overviews introduces additional complexity. Combining these factors leads to a complex learning task that might overwhelm the cognitive system of learners and apparently our intervention did not help to overcome this problem. Our findings impact the applicability of graphical overviews and our intervention in real learning situations. Based on the results, graphical overviews seem to be more suited for well-defined problems and we think graphical overviews should be used with caution when the learning setting is already known to be difficult for learners, for example when the learning goal is not clear to them.

Tool Use in Technology-Enhanced Learning

In our first study, participants did not work with our tools as we had expected. This phenomenon of inconsistencies between intended and actual use of computer tools was also described by Clarebout and Elen (2009). They stated that learners must be knowledgeable and willingly to use a support device. Similarly, Winters, Greene, and Costich (2008) summarized in their review of 33 empirical studies on self-regulated learning with CBLEs that “while students may have viewed support tools as aiding their SRL, they did not always use tools and supports available to them” (p. 438). In our first study, participants tried to understand complex topics, without addressing the prerequisite topics first. Apparently, participants preferred to directly navigate to the end goal when that goal was clear. In our study, the purpose of the tools was explained, however, it appeared that the tools did not have the affordance to address a number of sources to reach a learning goal. One explanation of this behaviour could be that participants were not used to approaching learning material in this way. Our findings subscribe the statements made by Jonassen (1993), who stated that merely visualizing the learning domain in a CBLE does not automatically change cognitive processes in such a way that it would lead to better structured knowledge. Learners must also be encouraged to actively process the available information. Although navigational behaviour was influenced for well-structured tasks, no evidence was found to confirm our expectations that visualization of prerequisites would lead to more connected understanding and that this would lead to better task performance. Results from the first study have a similar pattern as the results of Bolman et al. (2007), who found that most participants followed their advice and that the advice stimulated them to continue working on the course. However, they found no correlation between following their advice and the eventual results. In their study, they measured whether participants actually completed the course. To better direct the behaviour of the participants in our second and third study towards planning, we added an explicit planning component to our tool. We observed that this component heavily influenced the way participants approached the learning domain. In the first study, participants mainly read the goal documents without giving the prerequisites appropriate attention. In the third study, the amount of time was more evenly distributed over all learning material. However, based on our findings we cannot conclude whether this "better" approach to the learning material actually led to improved learning outcomes.

6.4 *Recommendations for Future Research*

A considerable amount of literature has been published on SRL. However, there is little empirical research on the specific effects of planning on learning. As self-regulated learning is becoming more popular in schools and companies, it is remarkable that we do not fully understand the consequences of all aspects of such approaches on learning yet. Some studies have demonstrated a correlation between planning activities and academic achievement. For example, in their study on the role of SRL on students' understanding, Azevedo, Guthrie, and Seibert (2004) classified participants who showed large gains in conceptual understanding as high-jumpers, and those who showed little or no gain as low-jumpers. They found that high-jumpers performed significantly more planning activities during their learning. Although such studies provide an indication of the importance of planning on learning, they do not demonstrate that planning leads to better learning, but only that there is a correlation between planning and success in learning. Experimental approaches are required to examine whether the introduction of SRL to learners who would not perform such processes by themselves actually improves learning. The use of computers in education complicates the subject even more. Research on technology-enhanced learning touches both areas of education and computer technology. Mixed findings in the literature indicate a need for a more comprehensive research framework that not only includes SRL aspects, but also contextual aspects, such as characteristics of CBLEs, for example the type of assignments and the amount of learner control and support provided by the CBLE. Without such an overarching framework it is difficult to compare research studies and draw generally applicable conclusions on SRL and TEL. Moreover, research shows that several aspects of the learning environment influence learning. For example, Robinson et al. (2003) found that the size of the learning domain influenced learning. Therefore, we must be cautious to generalize these findings to different visualizations of the instructional information and learning domains. Besides the components that are already addressed in SRL, we think that task aspects and learning environment aspects should also be included in the framework. This is similar to the suggestion made by Rouet (2009). Figure 25 shows a graphical representation of the different aspects that are important for such an overarching framework.

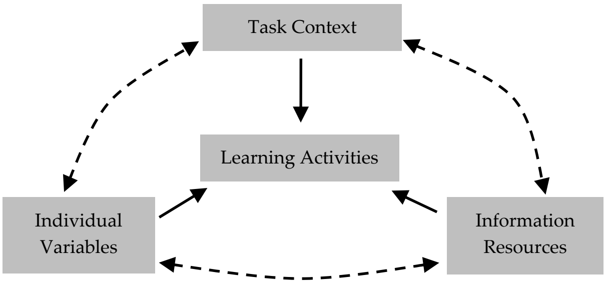

Figure 25. Research framework based on Rouet (2009).

The inconsistencies between actual learning outcomes and perceived learning outcomes, raise questions about relying on self-reporting measurements. Based on our findings, an objective measure of learning outcomes should always be included in a study, because learners found it difficult to judge how well they actually learned. In our study, we asked learners with which tool they learned most. A possible explanation of our finding is that learners might have interpreted our questions differently than we intended. "Learning" can be interpreted as an activity, but also as a learning outcome. An interesting extension of our research is the use of a knowledge test conducted after a few weeks, because the difference in structural knowledge measured in our second study and the differences in reported learning activities might lead to knowledge differences in the long term. Moreover, it would be interesting to observe learners who are free to select which tools they want to use. Participants in all studies described in this dissertation were behavioural science students. Students are assumed to have above average cognitive and verbal skills and reading ability. Accordingly, we must be careful with the interpretation and generalization of our findings to other less homogenous groups. Future research could also address the use of planning in CBLEs that aim at younger learners.

In our study, we used one particular type of graphical overview and one specific way of describing prerequisite relationships. However, planning can be performed in many different ways. It can be performed with simple resources, such as pen and paper, but it can also be performed with advanced software tools or CBLEs. Furthermore, planning can involve not only the content or sequence of the learning material, but also the learning processes that are going to be performed and aspects such as time. For example, learners can choose whether they want to practise, to study learning material, to rehearse, etc. The use of such different approaches to the planning process assumably influences the effectiveness of that process. In our studies, the planning addressed brief learning sessions. Whereas we found no differences on the eventual learning outcomes of these brief sessions, the effect of planning on larger learning sessions might be different. Therefore, we suggest to test the effects of planning on learning sessions that span a longer time period.

6.5 Conclusion

The studies performed in this research project provide insight in the effects of planning one's learning and the effects of visualizing prerequisites on learning. Based on our findings, we can now answer the research questions stated in the introductory chapter.

> Question 1. *Does the visualization of prerequisites in graphical overviews guide navigation through the learning domain and does it lead to better task performance and more knowledge?*

Visualization of prerequisites in graphical overviews guided navigation only when learners worked on well-structured problems. It did not guide navigation when learners were faced with ill-defined problems. Moreover, the visualization did not result in better task performance or better factual or conceptual knowledge.

> Question 2. *Do learners learn more when they are actively involved in the planning process, compared to when they are provided with automatically generated plans?*

Based on the second study, we concluded that learners gained structural knowledge from actively planning the learning process. However, these positive effects on the structural knowledge were not visible anymore at the end of the learning process. As expected, we found that participants sooner started with the learning phase when the tool created the planning for them. We also found that with the CG-tool, learners also attained more to the graphical overview in the course of the learning process, compared to when they used the LG-tool. Accordingly, participants who actively created their learning plans had better structural knowledge at the start of the learning phase. However, they did not look at the graphical overview in the rest of the learning process anymore. When participants received a planning, they seemed to regulate their structural knowledge by giving more attention to the graphical overview. At the end of the learning process, there was no difference between the tools for structural, conceptual, or factual knowledge. Remarkably, like in the second study, participants in the third study also indicated that they thought they had learned most from actively constructing the plan and that they would prefer to perform active planning when the plans were to be used by themselves. So, although we found no differences in the factual, conceptual, and structural knowledge at the end of the learning process, participants still thought that they learned more from the LG-tool, and they preferred to use that tool for their own learning. As the second study demonstrated that active planning led to more structural knowledge directly after the planning process, it remains the question how this effect can be utilized to improve the whole learning process.

Mixed findings in research indicate that there is not a profound understanding of the interaction of computers and learning yet. Although several SRL models have emerged by this time, it remains difficult to link technological features to these models. As such new technologies are applied in the development of CBLEs, it is not evident what the effects of such technologies on learning are. The danger of such a situation is that newly introduced technologies could be used on a large scale, while they are actually disadvantageous for learning. Our study contributes to the idea that learner control does not automatically lead to improved learning outcomes, and that some external regulation can support the learning process. We found no effect of active planning on eventual learning outcomes. Based on findings in our studies, it is tempting to conclude that regulative activities can simply be taken over by computers, without affecting learning outcomes. However, literature and subjective ratings of participants in our studies suggest that participants prefer to perform such activities themselves. Therefore, we think that learners' self-efficacy and long term motivation will be positively influenced when they think that they are in control of learning and that the activities that they perform help to better understand the learning material, even when that is in reality not the case.

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Chapter 7

Nederlandse Samenvatting

7.1 *Inleiding*

Het onderzoek dat in dit proefschrift wordt beschreven had tot doel om inzicht te krijgen in de effecten van plannen op leren. We hebben onderzocht of het actief plannen van het leerproces effect had op leerresultaten. Bij actief plannen bepaalden de deelnemers zelf in welke volgorde onderwerpen in een elektronische leeromgeving werden geleerd. Bij passief plannen werd de volgorde van de onderwerpen door de leeromgeving bepaald en werd het resultaat hiervan aan de deelnemers getoond. Voor het leren van conceptuele kennis is het voor de lerenden van belang een overzicht van het lesmateriaal te hebben, zodat de relaties tussen de verschillende onderwerpen duidelijk zijn en nieuwe kennis beter kan worden geïntegreerd in bestaande kennis. De aanname hierbij is dat kennis die op een dergelijke geïntegreerde manier wordt opgeslagen beter is dan kennis die geïsoleerd wordt opgeslagen. Om een dergelijk overzicht te geven kan gebruik worden gemaakt van een zogenaamd grafisch overzicht, waarin de onderwerpen uit het lesmateriaal in een figuur worden getoond. Bij dit onderzoek maakten deelnemers een planning op basis van dergelijke grafische overzichten. In deze overzichten werden de beschikbare onderwerpen en de relaties tussen deze onderwerpen getoond. De onderwerpen werden dus niet op een lineaire manier, maar als een samenhangend netwerk van onderwerpen weergegeven. Via de onderwerpen in het grafisch overzicht, konden de lerenden lesmateriaal over dat onderwerp benaderen. Op deze manier konden ze niet-lineair door het materiaal heen navigeren en tegelijk overzicht over het materiaal houden. Ondanks dat vele onderzoeken hebben aangetoond dat leerprestaties bij het leren met grafische overzichten kunnen verbeteren, zijn er ook problemen bekend met betrekking tot het gebruik van grafische overzichten in het leerproces. Juist omdat het materiaal niet lineair wordt weergegeven is het lastiger om te bepalen men naartoe wil navigeren en welke onderwerpen al geleerd zijn en welke nog niet. Lerenden zouden dus het overzicht in het materiaal kwijt kunnen raken. In het Engels wordt dit aangeduid met de sprekende term “lost in hyperspace”. Dit soort negatieve aspecten van grafische overzichten zouden problemen op kunnen leveren met als mogelijk gevolg dat leerresultaten bij het werken met dergelijke omgevingen negatief kunnen worden beïnvloed.

Eerste studie

Bij het eerste, verkennende onderzoek is gekeken naar de effecten van het tonen van instructionele informatie op het navigatiegedrag, op kwaliteit van taakuitvoering en op leerresultaten van deelnemers. De instructionele informatie bestond uit een visualisatie van vereiste voorkennis tussen verschillende onderwerpen. Het doel van het visualiseren van voorkenniseisen, was dat deelnemers bij het navigeren in het grafisch overzicht deze informatie zouden gebruiken om een weg door het grafisch overzicht te zoeken. Het was de verwachting dat lerenden door het tonen van deze informatie een meer gedegen route door het leerdomein zouden kiezen en dat ze hierdoor het materiaal beter zouden leren. Een mogelijk nadeel van het tonen van dergelijke informatie was dat het grafisch overzicht er visueel complexer van werd. Omdat navigeren op zichzelf al een cognitief belastende taak is, kan de belasting nog hoger worden naarmate het grafisch overzicht complexer wordt. In het onderzoek werd aan deelnemers gevraagd een taak op te lossen. Ze dienden daarbij gebruik te maken van een ondersteunende tool met een grafisch overzicht, waarin voor de taak relevante onderwerpen werden getoond. De taken waren zodanig ontworpen dat de deelnemers informatie moesten opzoeken en begrijpen om de taken correct te kunnen uitvoeren. Uit de resultaten van de studie kwam naar voren dat het tonen van de voorkennisrelaties tussen onderwerpen in het grafisch overzicht het navigatiegedrag positief beïnvloedde, maar alleen bij duidelijke gestructureerde (well-structured) opdrachten. Met *duidelijk gestructureerde opdrachten* worden in dit onderzoek opdrachten bedoeld waarbij het einddoel al uit de vraagstelling af te leiden was. Bij ongestructureerde (ill-structured) opdrachten was dat niet het geval. De lerenden moesten hier zelf actief op zoek naar het einddoel. Een mogelijke verklaring waarom de gebruikte interventie geen invloed had op het navigatiegedrag bij ongestructureerde opdrachten is dat de navigatietaak samen met de extra getoonde informatie een dermate hoge cognitieve belasting opleverden dat deelnemers de getoonde informatie niet meenamen in het navigatieproces. Uit de resultaten bleek dat er tussen de twee vergeleken tools geen verschillen waren in de leerresultaten van de lerenden en ook niet in de kwaliteit van de taakuitvoering. Bij nadere analyse van het navigatiegedrag werd het duidelijk dat deelnemers slechts kort gebruik maakten van de ondersteunende tools en dat ze vaak snel naar de uiteindelijke onderwerpen navigeerden, terwijl het de bedoeling was dat ze ook aandacht zouden schenken aan de onderwerpen die tot de vereiste voorkennis behoorden. Uit analyse van de uitgevoerde taken bleek dat deelnemers vaak niet over voldoende kennis beschikten en toch de taak probeerden uit te voeren. Om de aandacht sterker op het planningsproces te richten, hebben we in de tweede en derde studie het plannen expliciet in de tools opgenomen.

Tweede studie

Op basis van de ervaringen van het eerste onderzoek is het plannen van het leerproces expliciet aan de tools toegevoegd. In de tweede studie stelden deelnemers zelf een plan op of ze kregen een automatisch gegenereerde planning gepresenteerd. Deelnemers kregen een vastgestelde tijd om aan de planning te werken om een leerdoel te bereiken en deze te planning bestuderen. In beide gevallen werd het uiteindelijke leerdoel door de tools bepaald. Zodra de gegeven tijd was verstreken werd de kennis over het grafisch overzicht getoetst. Het kennisniveau werd dus direct na het opstellen van het plan gemeten, maar voor het daadwerkelijke uitvoeren van het leerproces. Uit de resultaten kwam naar voren dat de deelnemers slechtere plannen maakten dan de computer, dat wil zeggen dat, op basis van de gedefinieerd voorkenniseisen, de plannen van de deelnemers niet altijd correct waren en die van de computer wel. Dit hadden we niet verwacht, omdat de tools aanwijzingen gaven om tot een correcte planning te komen. Ondanks dat de opgestelde plannen niet altijd correct waren met betrekking tot de vereiste voorkennisrelaties, hadden de deelnemers een betere, correcte kennis van de structuur van het domein wanneer ze zelf actief de plannen hadden opgesteld, vergeleken met wanneer ze de plannen gepresenteerd kregen. Na het actief plannen wisten de deelnemers dus meer over de globale structuur van het leerdomein. De deelnemers gaven daarbij wel aan dat het actief opstellen van de planning tot een hogere taakbelasting leidde. Er waren geen verschillen in de opgedane feitenkennis over het leerdomein. Het verwerven van de structurele kennis en de hogere gerapporteerde taakbelasting hadden dus geen negatieve invloed op het verwerven van feitenkennis.

Derde studie

In de tweede studie vonden we dat deelnemers een betere kennis van de structuur van het leerdomein hadden als ze zelf hun leerplan hadden opgesteld. Op basis van klassieke leertheorieën, zoals de Subsumption theorie van Ausubel, verwachtten we dat deze kennis van de structuur van het domein zou bijdragen aan het daaropvolgende leerproces. In het derde experiment hebben we de tool van het tweede experiment toegepast in het gehele leerproces. Bij dat experiment werd de planning wederom opgesteld door de deelnemers zelf of door de computer, maar vervolgens werd deze planning gebruikt om het leerproces daadwerkelijk uit te voeren. Het lesmateriaal werd daarvoor in de volgorde gepresenteerd die in de planning was vastgelegd. Ondanks dat de deelnemers aangaven dat ze zowel meer structurele als inhoudelijke kennis hadden opgedaan toen ze zelf de planning opstelden, kwam dit niet tot uitdrukking in de resultaten van de afgenomen kennistoetsen. Bij de toetsen was geen verschil te zien in feitenkennis, conceptuele kennis, maar ook niet meer in de structurele kennis. Er zijn verschillende mogelijke verklaringen voor het verdwijnen van de voorsprong in structurele kennis. Een mogelijke verklaring kan worden gegeven op basis van het geobserveerde gedrag in de tools. Wanneer deelnemers zelf een plan moesten opstellen, gingen ze direct aan het begin van het leerproces actief aan de slag met de elementen in het grafische overzicht. Wanneer ze echter een plan kregen aangereikt, gingen ze vrijwel direct aan de slag met het doornemen van het lesmateriaal. Opvallend is dat deelnemers die een plan gepresenteerd kregen, juist in de loop van het leerproces meer aandacht aan het grafische overzicht gaven. Het leek er dus op dat ze de achterstand in structurele kennis in de eerste fase van het leerproces compenseerden door in de uitvoerende fase van het leerproces meer aandacht aan het grafisch overzicht en dus de structurele kennis te geven. Bij de derde studie was het de verwachting dat lerenden meer kennis zouden hebben als ze de planning zelf hadden opgesteld, maar dit werd niet door de resultaten bevestigd. Op basis van de resultaten van de kennistoetsen kunnen we concluderen dat het voor het uiteindelijke kennisniveau niet uitmaakt of lerenden actief of passief plannen.

7.2 *Discussie en Conclusie*

Op basis van de resultaten van de hierboven beschreven studies kunnen we een aantal uitspraken doen over de effecten van actief plannen op het leerproces. Zelfregulatie is een moeilijk proces, en wanneer je dit als lerende naast je leertaken uitvoert, dan kan dit de leertaken negatief beïnvloeden. Uit de literatuur kwam naar voren dat vooral lerenden met beperkte zelfregulatievaardigheden of met beperkte voorkennis van het leerdomein meer moeite zullen hebben met het uitvoeren van al deze taken. Bij hen zal het cognitieve systeem sneller overbelast raken. In onze eerste studie hebben we de effecten van een hulpmiddel in grafische overzichten geëvalueerd. Dit hulpmiddel bestond uit het tonen van vereiste voorkennis in het grafische overzicht. Uit de studie kwam naar voren dat dit hulpmiddel alleen hielp bij goed gestructureerde opdrachten, waarbij de oplossing al uit de vraagstelling kon worden afgeleid. In de tweede en derde studie werd het leerdoel aan het begin van de sessie gegeven. Dit soort opdrachten kwam dus overeen met de goed gestructureerde opdrachten uit de eerste studie. Op basis van de tweede studie kan worden geconcludeerd dat actief plannen een zwaardere taakbelasting oplevert dan passief plannen. Dit is niet verwonderlijk, want de deelnemers voerden extra cognitieve handelingen uit. In de derde studie vonden we echter dat wanneer het plannen in het totale leerproces werd geïntegreerd, er geen verschillen meer waren tussen de taakbelasting bij de twee vergeleken tools. Dit kan op een aantal manieren worden verklaard. Het zou kunnen dat plannen weinig bijdraagt aan de totale taakbelasting, maar op basis van de hoeveelheid tijd die deelnemers in het planningsproces staken lijkt dit niet aannemelijk. Een andere verklaring is dat het leren van het materiaal makkelijker gaat wanneer je zelf hebt gepland en meer kennis van de structuur van het domein hebt. Deelnemers gaven zelf aan dat dat inderdaad het geval was. In ieder geval levert actief plannen, zoals in deze studies geïmplementeerd, dus geen extra belasting op voor het gehele leerproces. In de literatuur worden activiteiten zoals zelf plannen binnen SRL over het algemeen als positief voor het leren beschouwd. Een nadere beschouwing van de literatuur liet echter zien dat er nauwelijks empirische onderbouwing is voor dergelijke uitspraken. Naast studies waarin de correlatie tussen succes in leren en plannen werden meegenomen, hebben we geen experimenten gevonden waarbij het planningsproces werd gevarieerd en de effecten op het leerresultaat werden gemeten. In dit experimentele onderzoek hebben we gekeken of actief plannen van het leerproces een positieve invloed had op leren.

Uit de literatuur over *learner control* kwam naar voren dat actief plannen tot een hogere motivatie zou kunnen leiden, omdat deelnemers bij actief plannen meer invloed op het leerproces kunnen uitoefenen. In de derde studie hebben we motivatie gemeten direct na het werken met beide tools, maar we vonden hier geen significante verschillen tussen de twee vergeleken tools. Opvallend genoeg hadden de deelnemers wel een uitgesproken voorkeur voor welke tool ze zouden willen gebruiken in hun eigen leerproces. In zowel de tweede als in de derde studie werd aan deelnemers gevraagd welke tool ze zouden willen gebruiken in twee hypothetische situaties: 1) als ze de planning voor hun eigen leerproces gingen gebruiken en 2) als de planning door iemand anders, bijvoorbeeld door een studiegenoot, gebruikt zou worden. In beide studies gaven deelnemers aan dat wanneer ze het leerplan voor hun eigen leerproces zouden gebruiken, ze de voorkeur hadden voor de LG-tool, dus voor actief plannen. Wanneer het plan voor iemand anders gemaakt zou worden, dan was er in de tweede studie geen meerderheid meer voor een tool, en in de derde studie een meerderheid (58,7%) voor de CG-tool, dus de tool waarin de computer de planning maakte. In de derde studie was er bij geen van de typen toetsen een significant verschil tussen de verschillende tools. Opvallend was dat de deelnemers wel een uitgesproken mening hadden over welke tool beter voor het leerproces was geweest. Bij de derde studie, gaf een meerderheid van de deelnemers aan dat ze zowel voor structurele als domeinkennis het meest hadden geleerd wanneer ze actief hun plan hadden opgesteld. Blijkbaar is er een verschil tussen de verwachtte kennis en tussen de daadwerkelijke opgedane kennis.

We weten niet waarom deelnemers de voorkeur hadden voor actief plannen wanneer ze zelf het plan zouden gaan gebruiken. Op basis van de gemeten motivatie kunnen we concluderen dat het werken met de LG-tool niet tot een hogere motivatie leidde, vergeleken bij werken met de CG-tool. Er waren wel verschillen met betrekking tot de kennis, direct na het opstellen van de planning. Deelnemers die actief hun planning hadden opgesteld hadden meer structurele kennis. Deze verschillen waren echter niet meer aanwezig bij de uiteindelijke leerresultaten. Deelnemers gaven echter aan dat ze dachten dat ze meer kennis hadden wanneer ze met de LG-tool hadden gewerkt. Dit zou kunnen verklaren waarom er een voorkeur voor actief plannen was; deelnemers hadden het gevoel dat ze er meer van leerden, ondanks dat dit niet daadwerkelijk het geval was. Nu rest de vraag of actief plannen beter is voor het leerproces dan passief plannen. Met andere woorden, als we een planning gebruiken in een elektronische leeromgeving, moeten we deze dan door de computer laten opstellen of door de gebruikers zelf? Op basis van de resultaten van de tweede studie kunnen we concluderen dat actief plannen direct een positieve invloed heeft op structurele kennis en geen (negatieve) invloed op feitenkennis. Op basis van de resultaten van de derde studie moeten we echter concluderen dat het actief plannen geen invloed heeft op uiteindelijke feitenkennis, structurele kennis, en conceptuele kennis. Als het daadwerkelijke leerresultaat dus het enige criterium is, dan maakt het niet uit welk type plannen wordt gebruikt. Bij actief plannen krijgen de lerenden direct aan het begin van het leerproces kennis van de structuur van het leerdomein. Bij passief plannen verwerven ze deze kennis in de loop van het leerproces. Ook vonden we geen verschillen in gemeten motivatie. Dit was opvallend, omdat we op basis van de literatuur verwachtten dat deelnemers een hogere motivatie zouden hebben als ze meer controle over het leerproces hadden. De resultaten van de derde studie onderschrijven deze gedachte echter niet. Uit het onderzoek kwam duidelijk naar voren dat deelnemers wel dachten dat ze meer hadden geleerd wanneer ze zelf hun plan hadden opgesteld. Als een elektronische leeromgeving in een echte leersituatie, zoals op school of op de werkvloer, wordt toegepast, dan is het aannemelijk dat actief plannen uiteindelijk toch een positieve invloed zal hebben op de motivatie en het zelfvertrouwen van de lerenden. Het geeft namelijk meer voldoening om een taak uit te voeren waarvan men denkt dat deze taak ook daadwerkelijk kennis oplevert. Als we dit meenemen in onze overweging, dan gaat de voorkeur uit naar het actief plannen, ondanks dat dit feitelijk niet tot betere leerresultaten leidt. Het blijft vooralsnog de vraag hoe we de positieve effecten van het actieve plannen die we in de tweede studie vonden kunnen gebruiken om het gehele leerproces effectiever en efficiënter te kunnen maken.

List of Acronyms

APOSDLE	Advanced Process Oriented Self-Directed Learning Environment. The overarching project in which this research was performed.
CAI	Computer Assisted Instruction.
CBLE	Computer-Based Learning Environment. A learning environment that runs as software on a computer.
DOW	Description of Work. Document that describes the work that will be done in a project.
EU	European Union.
ICT	Information and Communication Technology. In this dissertation, we focus on software for personal computers.
IPT	Information Processing Theory.
SDL	Self-Directed Learning. In SDL, individuals take the initiative for their learning, by selecting, managing and assessing their own learning.
SRL	Self-Regulated Learning. Similar to SDL, but SRL focuses more on the learning process. For a detailed comparison see (Loyens, et al., 2008).
TEL	Technology-Enhanced Learning, refers to the use of technology (often ICT) to support learning, teaching, and competency development.
WP	Work Package. A part of a project that addresses one or more specific topics.
WWW	World Wide Web. The internet.

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Wilco Bonestroo

Short Biography

Wilco Bonestroo was born on October 5, 1979 in Nunspeet. After finishing his secondary education at the Lambert Franckens College in Elburg in 1998, he studied Computer Science at the University of Twente. Wilco specialized in software engineering. He carried out his master thesis assignment at the Twente Research and Education on Software Engineering (TRESE) group, where he evaluated a domain specific programming language for Thales Naval Nederland. After Wilco graduated in Computer Science, he completed the Technisch Universitaire Lerarenopleiding, a course to become a mathematics teacher. There, he received the degree Master of Science of Teaching Mathematics (eerstegraads lesbevoegdheid in wiskunde). After his studies, Wilco worked at the Christelijke Hogeschool Windesheim in Zwolle, where he was an instructor for several courses, ranging from programming to graphical user interface design, and theoretical computer science.

In April 2006, Wilco started as PhD student at the University of Twente, Faculty of Behavioural Sciences, Department of Instructional Technology (IST). He participated in the EC 6th Framework Programme for Research and Technological Development (FP6) project APOSDLE, which stands for Advanced Process-Oriented Self-Directed Learning Environment. Goal of the APOSDLE project was to develop software to support learning at the workplace. Within the project, Wilco focused on planning tools to support self-directed learning.

After his PhD project, Wilco started at Xsens Technologies B.V. in May 2010. At Xsens, Wilco works as software engineer on MVN studio, a software product that allows users to easily record Motion Capture data. Motion Capture (or MoCap) is a way to record human movement. MVN Studio provides real-time visualization, playback and editing of such data. Wilco mainly focuses on the visualization of complex data, GUI design and implementation, and user interaction design.

Appendix – Guidelines from TEL Literature

In this appendix, we provide an overview of the guidelines by DeRouin, Fritzsche, and Salas (2004), Jacobson and Archodidou (2000), and Park and Hannafin (1993), respectively. In Chapter 2 these guidelines are addressed in more detail.

Table 14

Principles for Learning Control in Learning Environments.

Principle	Principle
Understanding Learner Control Is Half the Battle	Footprints Help ("You Are Here")
Give It Time	Create Smooth Transitions
Calibrate Expectations	Share Design Control
Offer Help	Be Consistent
What's Good for One Trainee May Not Be Good for Another	Keep Each Instructional Segment Self-Contained
More Isn't Necessarily Better	Promote It
"Skipping" Is Better Than "Adding"	Make It Matter
Keep It Real	Organizational Climate Matters

Note. This table is based on DeRouin, Fritzsche, and Salas (2004).

Table 15

Design Elements.

#	Description
1	Representational affordances of technology
2	Represent knowledge in context
3	Reify the deep structure of knowledge
3a	Abstract domain concepts
3b	Deep structure indexing and commentaries
3c	Conceptual visualizations
4	Intra- and intercase hyperlinks for conceptual and representational interconnectedness

Note. This table is based on Jacobson and Archodidou (2000).

Table 16

Design Principles for Multi-Media.

#	Description
1	Related prior knowledge is the single most powerful influence in mediating subsequent learning.
2	New knowledge becomes increasingly meaningful when integrated with existing knowledge.
3	Learning is influenced by the supplied organization of concepts to be learned.
4	Knowledge to be learned needs to be organized in ways that reflect differences in learner familiarity with lesson content, the nature of the learning task, and assumptions about the structure of knowledge.
5	Knowledge utility improves as processing and understanding deepen.
6	Knowledge is best integrated when unfamiliar concepts can be related to familiar concepts.
7	Learning improves as the number of complementary stimuli used to represent learning content increases.
8	Learning improves as the amount of invested mental effort increases.
9	Learning improves as competition for similar cognitive resources decreases and declines as competition for the same resources increases.
10	Transfer improves when knowledge is situated in authentic contexts.
11	Knowledge flexibility increases as the number of perspectives on a given topic increases and the conditional nature of knowledge is understood.
12	Knowledge of details improves as instructional activities are more explicit, while understanding improves as the activities are more integrative.
13	Feedback increases the likelihood of learning response-relevant lesson content, and decreases the likelihood of learning response-irrelevant lesson content.
14	Shifts in attention improve the learning of related concepts
15	Learners become confused and disoriented when procedures are complex, insufficient, or inconsistent.
16	Visual representations of lesson content and structure improve the learner's awareness of both the conceptual relationships and procedural requirements of a learning system.
17	Individuals vary widely in their need for guidance.
18	Learning systems are most efficient when they adapt to relevant individual differences.
19	Metacognitive demands are greater for loosely structured learning environments than for highly structured ones.
20	Learning is facilitated when system features are functionally self-evident, logically organized, easily accessible, and readily deployed.

Note. This table is based on Park and Hannafin (1993).

The ongoing developments in computer technology have dramatically changed the way we work, live, and learn. This dissertation describes a series of experimental studies that focused on the effects of support tools on self-regulated learning. In the studies, university students worked with computer-based learning environments that visualized complex learning domains as networks of interrelated concepts. For every node in the network, the learning environment contained learning material. To study the available learning material in a structured way, students used learning plans that can be conceptualized as routes through the network of concepts. This dissertation addresses the effects of such software on learning.