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Effects of planning on task load, knowledge, and tool preference: a comparison of two tools

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Self-regulated learners are expected to plan their own learning. Because planning is a complex task, it is not self-evident that all learners can perform this task successfully. In this study, we examined the effects of two planning support tools on the quality of created plans, planning behavior, 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. The results indicated that the quality of learner-created plans was lower than computer-generated plans. Furthermore, participants reported a higher task load when they constructed the plans by themselves. However, participants gained more structural knowledge about the learning domain when they actively created plans. There was not an apparent preference for one 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 plans.

Keywords: self-regulated learning; cognitive tools; learning strategies; active learning; graphical overviews

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 (SRL) (Azevedo, Moos, Greene, Winters, & Cromley, 2008; Dinsmore, Alexander, & Loughlin, 2008). Regulation includes planning, performing, monitoring, and evaluating the process. Although planning is an important phase in the learning process, there is not much research done 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.

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The role of planning in self-regulated learning

Several models describe the SRL process. In their comparison of five well-known models, Puustinen and Pulkkinnen (2001) concluded that all models identified three phases in the SRL 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 SRL, however, 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 are understood before other topics are learned. In this case, topics have a prerequisite relationship to 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, that the prerequisite relationships are adhered to. Early chapters contain basic knowledge, whereas later chapters contain advanced knowledge that builds on that basic knowledge. Interactive learning material, such as websites, simulations, and electronic documents, is often not designed to be accessed in a sequential order. Thus, to access the material in an effective way, someone must decide how to work through the material.

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. Planning does not only influence 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 behavior. 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 an increased academic success of 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 identified that increased learner control in combination with non-linear learning environments can lead to problems such as disorientation and cognitive overload (Scheiter & Gerjets, 2007; Shapiro, 2008). To prevent such problems, learning control can be reduced by, for example, letting software make decisions for learners. From a usability perspective, this would reduce the effort for users 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, from the literature it becomes clear that strategies that aim at the preparatory phase play a crucial role in the learning process. Furthermore, it appears that SRL generally has a positive inclination. Closer inspection, however, reveals that self-regulation is difficult to perform and can lead to problems. Previous research 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 no empirical data on the effects of planning on learning yet.

Supporting planning

In his meta-analysis, Hattie (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 SRL environments. However, as stated before, planning is difficult and inexperienced learners tend to make wrong decisions in 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 that 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 more often used ineffective strategies and applied less monitoring to the process. According to Bell and Kozlowski (2002), study 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 otherwise not have been performed.

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 to compare 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 themselves. 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 of 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 are.

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 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 labeled 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 dynamically change over time. In this way, graphical overviews can adapt to, for example, 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 on 55 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 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 describes that elements that are placed close to each other are interpreted as related and the similarity principle describes that elements that share visual characteristics are interpreted as belonging together.

Navigational aids and support can direct learners' behavior 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 lead to more domain-related browsing behavior. 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 to attach 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 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

SRL theories describe the preparatory phase of learning as an important phase in the learning process. Previous studies have found positive effects for goal setting and self-regulative activities. However, there is no empirical evidence on the effects of planning on learning yet. As SRL 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 planning or the planning should be presented to the learners. For this study, two tools were developed. 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 behavior, experienced task load, recall of structural knowledge, and recall of factual knowledge. With both tools, participants had to plan learning and inspect elements from the planning in the corresponding graphical overview.

The quality of learning plans was determined based on instructional information of 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, automatic 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 automatic 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 behavior. 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 acquaintance of factual knowledge. As actively involving learners in the process can lead to motivation for learning, it was expected that learners would prefer to use the tool in which they actively constructed the planning.

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 orders 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. In total, four learning domains were used. Two domains were about data analysis. One focused 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 two other domains were about computer science. One addressed scheduling and the other processes management. To avoid confusion, all domains were selected in such a way that they did not overlap with any of the other domains. Figure 1 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) to 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 contains 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

The participants were 65 first-year students of behavioral science, 54 females and 11 males. Their average age was 20 years (SD = 2.01). Students had not encountered the 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.

Measurements

The dependent variables were cognitive load, structural knowledge, factual knowledge, browsing behavior, and plan quality. Cognitive load was measured

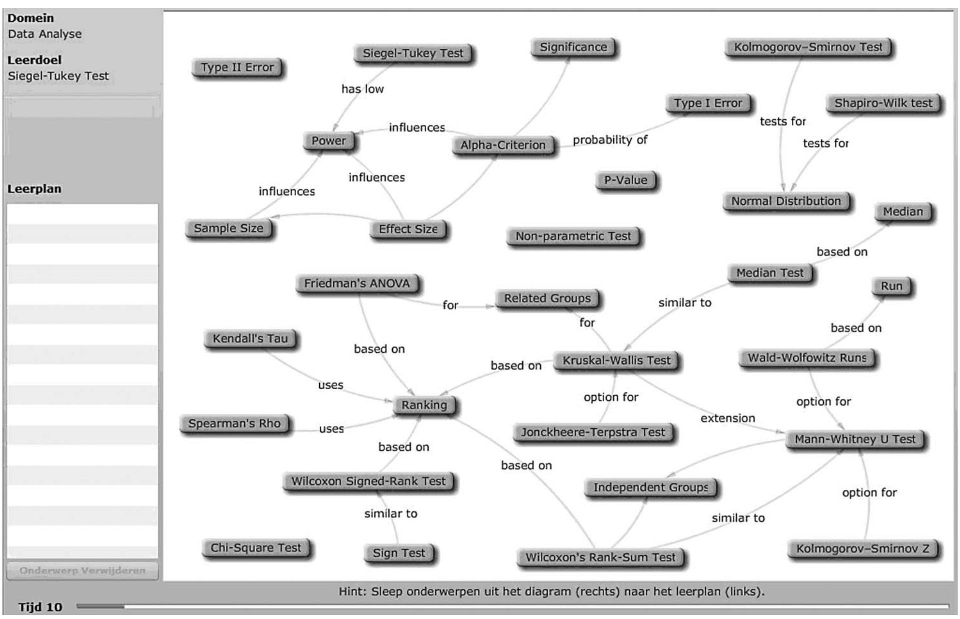

Figure 1. The planning tool with the learning goal (Leerdoel) and learning plan (on the left) and the graphical overview of the learning domain (on the right).

with an adapted version of the NASA Task Load Index (TLX) developed by Hart and Staveland (1988). The TLX combines ratings and weights and results in one score. The original version uses six 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 reduces the time required to fill-in the measure considerably. In this study, the TLX was used with five 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 get a maximum score of 16 points, and there were four factual questions for which they could get four points. Both tests were administered directly after completing a distracter task.

Browsing behavior 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 held their mouse pointer above a certain topic. The topics and amount of time for the display of tooltips was 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.

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 preferred 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 10–20 people. Sessions took 1 h 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 an example structural and factual knowledge test. Accordingly, participants knew what kind of questions to expect. The practice session took about 15 min in total. Then, each participant worked with all four domains. In every domain, they received two tasks. In every task a learning goal was provided. 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 ~ 10 topics from the domain and participants worked exactly 3 min with a plan. Within those 3 min, participants both had to 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

To test our research hypothesis, both parametric and non-parametric tests were used. 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 to measure preferences. Both pairs were analyzed with a McNemar–Bowker test to test whether there were differences between the provided answers (Bowker, 1948). All results are reported at a 0.05 level of significance. For each performed test with significant results an effect size estimate, r, is reported. Effect size estimates were calculated using to the techniques proposed by Rosenthal (1991).

Results

Two participants did not create any correct plan 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 resulting 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 (median = 4) than with the LG-tool (median = 4), $t = 25.50$, $p < 0.05$, $r = 0.37$.

Knowledge and task load

As expected, participants had more structural knowledge after working with the LG-tool than with the CG-tool. With the LG-tool, participants scored significantly higher on the structural questions (median = 25) than with the CG-tool (median = 23), $t = 25$, $p < 0.05$ (one tailed), $r = 0.16$. 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 (median = 2) compared to the LG-tool (median = 2), $t = 24$, $p > 0.05$ (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 ($M = 123.44$, $SD = 29.52$), $t(62) = 1.98$, $p < 0.05$ (one-tailed), $r = 0.28$.

Browsing behavior

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 (median = 337.16 s) than with the LG-tool (median = 342.67), $t = 29$, $p > 0.05$ (one tailed). Thus, with both tools participants spent approximately the same amount of time on reading text.

Table 1 displays the average times participants spent on reading relevant and irrelevant topics. The total time in each condition (each row) was 720 s. Participants could read text from relevant topics, irrelevant topics, or not read text at all. To test whether there were effects of the tool, a two-way repeated measures ANOVA was performed. There was no main effect for tool use, $F(1, 62) = 1.36$, $p > 0.05$. Furthermore, there was no interaction effect between the tool that was used and the relevance of the read texts, $F(1, 62) = 2.47$, $p > 0.05$.

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 2. There was a significant difference between the participants' answers for structural and factual knowledge, McNemar–Bowker $\chi^2(6, N = 63) = 31.62$, $p < 0.05$. The majority of the participants (87%) thought that they had gained more structural knowledge in the LG condition. For the factual knowledge, however, there was not an apparent preference for one of the conditions.

Table 1. 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 2. Perceived knowledge for factual and structural knowledge.

	Factual knowledge				
	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 conceptual knowledge. For example, 22 participants thought that they learned most factual knowledge from the LG-tool and most structural knowledge from the CG-tool.

Participants were also asked which tool they would prefer in two situations. The results are shown in Table 3. There was a significant difference between the participants' answers for the two hypothetical situations, McNemar–Bowker χ^2 (3, $N = 63) = 8.15$, $p < 0.05$. When participants had to make a plan for their own learning, most participants (71%) preferred the LG-tool to the CG-tool. However, when participants had to make a learning plan for someone else, there was not an apparent preference for one of the tools.

Conclusions 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 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 in which tool 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 only when they were to use the 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, support the learning process.

Table 3. 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%)

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 a 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 SRL 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. Quality of the plans created with the LG-tool was lower than 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 is expected that when learners receive more instructions on how to create correct plans, 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 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 exposure time 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 a more domain related browsing behavior. However, results do not reveal different behaviors for the tools.

There are some aspects we should keep in mind when interpreting findings from this study. First, this study focused on effects of planning processes. The actual performance phase of learning, normally following 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, it remains the question whether this small effect in the initial phase of learning eventually yields to larger gains in the whole 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 on 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 be negative for learning. Future research should include the whole process in which the learning plans are created and updated as learning proceeds. Fourth, the quality of the plans was determined based on the pedagogical information in the domains. Sometimes, instructional information is complex and is difficult to express in the domains. For example, in the current domains it was not possible to express that superficial knowledge of one topic was needed to understand another topic. The quality of suggestions made by automatic systems depends on the quality and expressiveness of the used instructional models. 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 tools used in this study was that the planning tool was simple and effective.

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