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LEARNING COMPLEX SYSTEMS WITH SIMULATIONS IN SCIENCE EDUCATION

Abstract. This study examined the effects of different kinds of tasks in computer-based simulations. The simulations were set to support the understanding of the respiratory chain. The theoretical background was derived from various models of cognitive psychology and research work within the field of computer-based learning. The focus was on the interrelations between the types of task (problem tasks, worked-out examples) in computer-based simulations, learners' prior knowledge and cognitive load. 144 biology students participated in this study. In a pre-test the subjects' biological prior knowledge and self-reported computer ability were examined. Subsequent to the treatment, learning outcome was examined and the individual cognitive load was registered. The results revealed the advantage of worked-out examples as instructional help for simulations. Furthermore, the results point at the importance of prior knowledge for comprehension. Additionally, a high individual cognitive load had a negative effect on learning results in understanding.

INTRODUCTION

Modern educational technologies offer many opportunities to visualise complex and dynamic systems. They are supposed to provide learning processes from a constructive point of view, especially in science education. Many studies in the field of cognitive psychology focused on the effectiveness of different modes of presentation and their combination to foster deeper understanding and meaningful learning (Lewalter, 2003; Mayer, 2001; Schnotz & Bannert, 2003). When information is presented by a certain combination of words (text, spoken words) and pictures (still images, animations, videos), this presentation is expected to help build up a mental model about the complex dynamic system (Schnotz & Bannert, 2003).

This contribution focuses on the effectiveness of simulations, a special kind of interactive animations. In addition to animated pictures and texts, simulations provide interactivity for the learner by the means of parameter choice. On the one hand a parameter choice of simulations can be advantageous for understanding causal relations within the complex dynamic system (Euler, 1994; Haack, 1995; Schnotz et al., 1999), on the other hand these learning environments impose a high cognitive load on the learners' working memory (de Jong & Njoo, 1992; Schnotz et al., 1999). Therefore, different kinds of tasks may be helpful to prevent a cognitive overload and to ensure comprehension of the dynamic system while learning with computer based simulations (Leutner, 1993). Recent studies have shown that problem tasks are auxiliary to support learning with simulations in the field of biology (Nerdel, 2003). Worked-out examples are known to foster cognitive skill acquisition, especially for learners with no or low prior knowledge in a well-structured domain (Atkinson et al., 2000). The aim of this study was to analyse the effectiveness of simulations with integrated tasks (problem tasks or worked-out

examples) on the comprehension of the causal relations of a complex and dynamic biological system (inner membrane of mitochondria) and its processes (respiratory chain). In addition we were interested in the self-reported cognitive load of the learners while working with these simulations.

THEORETICAL BACKGROUND

1.1. Learning with simulations

Simulations are characterised by the learners' strong interactive engagement. The learner has to select relevant parameters to manipulate the processes and the final state of the presented dynamic system. By means of self-regulated interaction with the simulation the learner actively creates his own learning process. This self-regulated learning with simulations fosters the understanding of causal relationships better than solely learning with animation (de Jong & Njoo, 1992; Leutner, 1993; Schnotz et al., 1999). Furthermore, learning with simulations may be advantageous for learning motivation. But there is an aspect that can deteriorate learning outcome: Simulations impose a high demand on learners cognitive system (Schnotz et al., 1999). Especially learners with no or low prior knowledge supposedly suffer from a cognitive overload in their working memory. Since we attribute importance to the cognitive load theory in this context we want to consider some of its aspects in the following section.

1.2. Cognitive Load Theory

Cognitive Load Theory (CLT) (Chandler & Sweller, 1991; Paas et al., 2003; Sweller et al., 1998) differentiates three types of cognitive load: intrinsic cognitive load (IL), extraneous cognitive load (EL) and germane cognitive load (GL). The first type, the intrinsic cognitive load, is determined by the number of elements and their interrelations. High element interactivity imposes high cognitive demands on the learner. IL is low, if elements can be learned and understood independently of each other and without causal connections between them. IL cannot be influenced by instructional design. This assumption is based on human cognitive architecture. It can be divided into two interacting parts: working memory and long-term memory. The long-term memory is potentially unlimited and can store large amounts of information in form of schemata . However, no information processing can take place within LTM, nor can schemata that already exist in LTM be modified. Conscious information processing takes place in the working memory. The capacity is extremely limited: only 5-7 chunks can be held and processed at the same time. Schemata, as mentioned above, represent learners' prior knowledge about the content (Kalyuga et al., 2003). The schemata are supposed to reduce the cognitive demands on learners' working memory. A schema, which is retrieved from LTM into the working memory, can be treated as a single unit of information and minimises the cognitive load while processing new learning contents. Learners with

high prior knowledge of a given topic possess a large amount of cognitive schemata for this topic. Consequently, they are able to effectively process learning material with high element interactivity maintaining a low cognitive load. Learners with no or low prior knowledge of a given topic possess a small amount of schemata of the content. To understand the meaning of the learning material they have to keep a lot of single elements in their working memory to comprehend the interaction and causal relations between the elements of the presented system.

Therefore, we have to focus on the cognitive load induced by the learning material. This kind of cognitive load is called extraneous cognitive load (EL). EL restricts the learning process. If the learner has to carry out cognitive activities, which are not directly contributing to learning, they will constrict schema acquisition or schema automation. Instructional designers should keep in mind some effects that could decrease learning outcome by increasing the extraneous cognitive load, e.g. the split-attention effect (Brünken & Leutner, 2001; Chandler & Sweller, 1992; Mayer & Moreno, 1998), the modality effect (Mayer, 2001, 2003) or the redundancy effect (Sweller, 2002). Thus, adequate instructional designs should strive to reduce extraneous cognitive load in favour of the third type of cognitive load, the germane load. The germane cognitive load positively affects the learning process. Just like IL and EL, the learning material induces it. But unlike the extraneous cognitive load, the GL leads to schema acquisition and automation. Once acquired, schemata lead to a less intrinsic cognitive load of the same learning content.

To summarise, the limited resources of the working memory restrict learning outcome and comprehension . The three types of cognitive load (intrinsic, extrinsic and germane cognitive loads) accumulate to an over-all cognitive load. Whereas, the intrinsic load is fixed by the learners' expertise in a domain, the extraneous and germane loads are supposed to be reduced by proper instructional design. Hence, in the following section we want to consider instructional support for learners with low prior knowledge, learning with simulations. The presented tasks could be helpful to increase learning outcome and to initiate problem solving in complex domains.

1.3. Instructional support while learning with simulations: different kinds of tasks

To assist novices in self-regulated learning of complex systems with simulations and to prevent them from a high extraneous cognitive load and to ensure learning outcome and comprehension, special types of help integrated in simulations may be useful. Tasks and work assignments direct the learner's attention and help him to define his aims and what he wants to achieve (Leutner, 1993). Using problem tasks as instructional help in learning environments with simulations has proven to be effective in the field of biology (Nerdel, 2003). Problem tasks help the learners to focus on relevant parts of a complex system, to understand its function and to comprehend the causal relations between the elements (Prechtl & Nerdel, 2002). On the one hand, problem tasks offer special help with regard to the content of the learning environment. On the other hand, they prevent a random and explorative processing of the simulation. Problem tasks allow the learner to control his learning

activity. Considering recent studies in the field of expert learning there is another type of task with a large impact on fruitful problem solving for learners with low prior knowledge: worked-out examples (Atkinson et al., 2000; Renkl et al., 1997; Sweller et al., 1998). They are not designed to test the learner's comprehension of a subject. Worked-out examples consist of the problem or the task and a worked-out step by step answer of the problem, as well as the problem solution itself. Worked-out examples support learners in acquiring comprehension and problem solving expertise. Furthermore, worked-out examples are suited to reduce cognitive load (Renkl & Atkinson, 2003).

OBJECTIVES AND HYPOTHESES

Since simulations, according to the general assumption, foster compression of causal relations within complex dynamic systems they are supposed to be suitable to assist comprehension in the field of science education, especially with regard to complex dynamic systems in biology. The focus of our empirical study was on the effectiveness of simulations, in which we provided learners with different types of tasks to support them. We were especially interested in analysing the way in which worked-out examples foster deeper understanding in the context of learning with simulations. Based on CLT an interaction effect between the treatment and learners' prior knowledge was to be expected with regard to learning outcome and cognitive load. Our hypotheses, therefore, read as follows:

Hypothesis 1: Simulations with worked-out examples foster comprehension of the dynamic processes of the respiratory chain at the inner membrane of mitochondria more effectively than simulations with problem tasks. Worked-out examples are especially helpful for learners with low prior knowledge

Hypothesis 2: Simulations with worked-out examples decrease cognitive load more effectively than simulations with problem tasks. With regard to learners' prior knowledge, those learners with a small amount of cognitive schemata (low prior knowledge) should benefit from the worked-out examples that reduce the cognitive load, while learners with high prior knowledge experience a similar cognitive load with both types of tasks.

Hypothesis 3: The more (extraneous) cognitive load the learning environment imposes on the learner, the worse his comprehension of the subject matter is. Accordingly, the interrelation between cognitive load and comprehension is inversely proportional.

RESEARCH DESIGN & METHODS

1.4. Learning environments

To examine the hypotheses of the study, the research design comprised two groups, each working with a different kind of computer-based simulation. The topic of the computer-based instruction dealt with the respiratory chain of the inner membrane

of mitochondria. After receiving a common introduction to the topic of the respiratory chain, learners had to choose parameters within this biological system to explore the causal connections between the elements and processes at the inner membrane of mitochondria. Figure 1 shows a screenshot of the learning environment. At this HTML-site learners are supposed to choose the different system parameters. After a choice has been made, an animation depending on the elected parameters would start, showing the resultant process. The main difference between the two versions of the simulation was the type of support the learners received. To encourage self-regulated learning and comprehension of the subject matter we added different tasks to both variants of the learning environment. The first variant of the simulation featured tasks in which students had to solve a problem (see Figure 1, the problem is shown by clicking one of the buttons in the left column). The answer format to these questions was single-choice (another pop-up window is revealed by a mouse-click on one of the buttons in the right column) and the learner got feedback about whether he was right or wrong. The second version of the simulation featured worked-out examples to support the learners. Parallel to the first version, there was the problem to solve (see Figure 1), but the answers were entirely worked out by the instructors. They were designed to help the learner comprehend the answer in a step-by-step procedure. Furthermore, there were hints with regard to a meaningful parameter choice in this context.

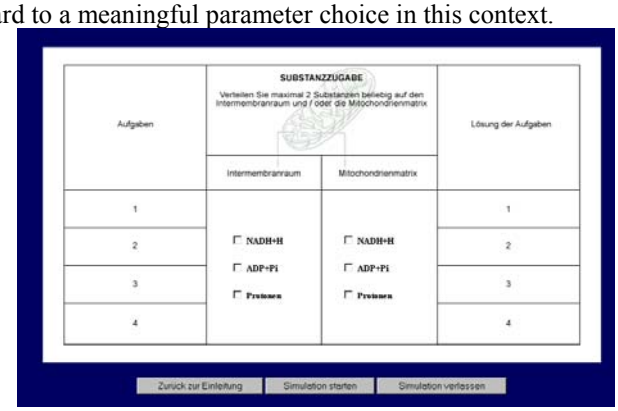

Figure 1: Screenshot of the simulation with parameter choice. A click on a button in the left column opens a pop-up window with a task to be handled with the simulation (for the parameter choice of the simulation, see the two columns in the middle of the figure). A click on one of the buttons in the right column opens a pop- up window where the task can be answered (further information, see text.)

1.5. Data collection

144 students from the universities of Kiel and Flensburg (Germany) took part in our study. They studied the field of biology to become teachers in German primary and secondary schools. The subjects were chosen from different semesters to reach a

large variety of prior knowledge. The sample consisted of 42 male and 102 female participants. Their age averaged M=22.9 years (SD=3.5 years).

All data was collected in a pre-post-test-design. The subjects were randomly allocated to the two different groups. In a pre-test at the beginning of the learning session prior knowledge of the respiratory chain was tested using 10 Items (7 items testing factual knowledge in general, 3 items testing factual knowledge in detail) in a single choice format. Furthermore, students were tested on their computer experience (18 items) using a 4-point answering scale. This questionnaire was supposed to be answered in 15 minutes. It was followed by a working period (roughly one hour) with the two different learning environments. After the treatment, the students were asked to complete a post-test questionnaire to register learning outcome distinguishing factual knowledge (identical items to pre-test) and comprehension (tested by 4 transfer items at medium and high level). Furthermore, the subjects were asked about their self-perceived cognitive load (8 items) and motivation (5 items) during the learning session, using a 5-point answering scale. Subjects had 15 minutes to fill in this questionnaire.

1.6. Data Analysis

To analyse learning outcome we distinguished between two categories: The increase of factual knowledge, in the following called facts, was defined as the difference between the sum score of the items testing factual knowledge in detail in post- and pre-test. Furthermore, understanding is defined as the sum score of the post-test items in this category. The last dependent variable cognitive load is defined as the mean of the relevant items of the post-test. Cluster analysis classified two different groups of prior knowledge (high and low). For the prior knowledge groups only the items of the pre-test in the category testing factual knowledge in general were analysed. The relations between the treatment (simulation with problem tasks, simulation with worked-out examples) and the prior knowledge (low, high) were examined by two-way analysis of variance (ANOVA) (see also Results section below).

RESULTS

1.7. Hypothesis 1: Instructional help via worked-out examples for understanding and especially for low prior knowledge

We wanted to know whether the simulation with worked-out examples is generally helpful to foster understanding and if it is especially useful to help subjects with low prior knowledge to learn about the subject matter. Therefore, we conducted a two-way analysis of variance for the variables *facts* and *understanding* to examine the main effect of the treatment and the interaction between the factors *kind of task (simulation PT, simulation WE)* and *prior knowledge (low, high)*. We found a non-significant main effect for *kind of task* ($F(1,140) = 2.25$ n.s., see Table 1) with regard

to *facts*. Subjects with low prior knowledge profited most from the worked-out examples for acquiring factual knowledge. However, the interaction effect between the factor *kind of task* and *prior knowledge* was not significant ($F(1,140) = 0.67$ n.s.). In contrast to this result the worked-out examples did not foster understanding better than the problem tasks when learning with simulation. The main effect *kind of task* was not significant ($F(1,140) = 0.01$ n.s.) with regard to *understanding*. Instead, prior knowledge generally led to a better understanding of the topic respiratory chain (main effect *prior knowledge* $F(1,140) = 2.70$, $p=0.100$). Subjects with high prior knowledge took advantage of the worked-out examples, while subjects with a low prior knowledge level could profit from problem tasks. The interaction effect between the factors *kind of task* and *prior knowledge* was not significant ($F(1,140) = 2.35$, n.s.). The descriptive statistics for *facts* and *understanding* are shown in Table 1.

Table 1: Learning outcome facts and understanding depending on kind of task (simulation PT, simulation WE) and prior knowledge. Sample (N), mean (M) and standard deviation (SD) are shown.

Learning outcome	*kind of task*	*prior knowledge*	*N*	*M*	*SD*
facts	simulation PT	low	31	0.52	1.26
		high	43	0.49	0.98
	simulation WE	low	33	0.97	1.24
		high	37	0.62	1.21
understanding	simulation PT	low	31	1.52	0.89
		high	43	1.53	1.05
	simulation WE	low	33	1.27	0.98
		high	37	1.81	1.08

1.8. Hypothesis 2: The effect of worked-out examples in simulations on cognitive load with regard to different levels of prior knowledge

The two-way analysis of variance showed a significant main effect for the factor *treatment* ($F(1,138) = 4.58$ $p<0.05$) as well as a highly significant main effect for the factor *prior knowledge (low, high)* ($F(1,138) = 8.45$ $p<0.01$). As a consequence, subjects with low prior knowledge learning with simulations with worked-out examples were at a disadvantage compared to the other groups. This group suffered from the highest cognitive load. Sample (N), mean (M) and standard deviation (SD) are shown in Table 2.

Table 2: Cognitive load depending on kind of task (simulation PT, simulation WE) and prior knowledge. Sample (N), Mean (M) and standard deviation (SD) are shown.

kind of task	*prior knowledge*	*N*	*M*	*SD*
simulation PT	low	30	1.85	0.65
	high	43	1.47	0.74
simulation WE	low	32	2.09	0.78
	high	37	1.76	0.69

1.9. Hypothesis 3: Interrelation between learning outcome and cognitive load

To revise the interrelation between the dependent measures of learning outcome and cognitive load we calculated Pearson's correlations. There was a small positive correlation between the learning outcome in factual knowlegde (facts) and cognitive load, but it was not significant ($r=0.105$, p n.s.). However, cognitive load correlates (highly) significant negative with the dependent measure understanding ($r=-0.226$, $p<0.01$).

DISCUSSION

Considering the first hypothesis, it was assumed that simulations with worked-out examples are superior to simulations with problem tasks in fostering comprehension of the topic respiratory chain. However, the results of the study indicate that simulations with worked-out examples foster factual knowledge, whereas they are not suitable to facilitate understanding. Furthermore, taking prior knowledge into account, there are some more interesting effects contradicting the first hypothesis: Simulations with worked-out examples promote factual knowledge for persons with low prior knowledge. In contrast, this learning environment is not able to stimulate comprehension better than simulations with problem tasks. For persons with high prior knowledge the results are inverse. Experts learn nearly the same amount of factual knowledge in both groups, but the simulations with worked-out examples are superior with regard to comprehension. Consequently, hypothesis 1 is to be rejected.

We want to focus on a model of multimedia learning developed by Schnotz and his co-workers (Schnotz & Bannert, 2003) to make a statement on these surprising results. The processing of text and pictures occurs separately with regard to the presentation. According to the model, the learner takes information from the text, constructs a mental representation from the text surface structure and establishes a propositional representation of the semantic content, i.e. a text basis. Eventually he generates a mental model of the topic of instruction. The construction of the mental model deriving from the text is guided by cognitive schemata which have selecting and organising functions. It has to be kept in mind that the propositional representation is close to the text, whereas the mental model corresponds to a reduced mental image. The way from the propositional representation to the mental

model, the model construction, is reversible. The reverse way is called model inspection. Pictures are cognitively processed in two-step procedure to eventually construct a mental model. First, a visual mental representation of the picture's graphic display is noticed. Second, a mental model of the subject matter is constructed through semantic processing, again guided by cognitive schemata. This mental model is then connected with the propositional representations via model inspection. It is assumed that the information exchange between propositional representation and mental model via model construction and model inspection continues while learning. Additionally, various findings indicate that the construction of a coherent mental model is limited by the capacity of the working memory.

We want to discuss our findings on the basis of this cognitive model. Persons with high prior knowledge possess a large number of cognitive schemata, which guide effectively the semantic processing of text surface structure into a propositional representation as well as processing of the perceived elements of a picture to a mental model. The mental model resulting from the text processing is coherent with the mental model deriving from the pictures of the learning material, as the same cognitive schemata controlling the selection and the organisation guide both processes. A similar argument could be used with regard to generating the propositional representations. The working memory of persons with expertise in the topic is less loaded with model construction and model inspection because only a small amount of new information for a deeper understanding can be selected according to goal-orientation and can be organised as well as integrated. Persons with high prior knowledge, thus, show only a small increase of factual knowledge, whereas their comprehension is more strongly supported. Persons with high prior knowledge are, as mentioned above, not supported by simulations with problem tasks. Therefore, their mental model deriving from text and the one deriving from pictures are not equal but complementary. They are merged into a single mental model by model construction and model inspection.

Persons with low prior knowledge posses only a few cognitive schemata to guide the cognitive processing of words and pictures. The worked-out examples were supposed to help these learners build up a coherent mental model and cognitive schemata that are helpful to understand the biological process in future learning situations. Persons with low prior knowledge working with simulations with worked-out examples are not goal-orientated in their collection of information and construct a propositional representation as well as a mental model without any references to each other. In favour of this explanation are the good results in factual knowledge of novices. Further processing, i.e. model construction and inspection, that leads to understanding is prevented by cognitive load of the working memory. In contrast, the animated sequences of simulation with problem tasks increased the understanding of the process efficiently. In this case, there is no interference between propositional representations deriving from text and those deriving from pictures. A single presentation mode (the pictures) relieves the working memory of inexperienced learners. Hence, a coherent propositional representation of the subject matter can be generated on the basis of common knowledge, whereas the causal

relations are interpreted correctly. Obviously, self-explanations of the mental model are more beneficial for novices than the presentation of a larger amount of information.

Hypotheses 2 and 3 assume that simulations with worked-out examples can take the cognitive load from learners' working memory (Renkl & Atkinson, 2003). In contrast, the results indicate that persons who had worked with simulations with worked-out examples generally felt a higher cognitive load. Novices working with simulations with worked-out examples experienced the highest cognitive load as well as the worst comprehension. The topic respiratory chain is very complex and, therefore, has a high level of element interactivity. As a consequence, the topic imposes a high intrinsic cognitive load on the learner. In addition, the simulation with worked-out examples causes an extraneous cognitive load. This leads to a decrease in comprehension. As mentioned above, simulations with problem tasks are sufficient for novices to point out the aims of the instruction and to facilitate their process of understanding. A further qualitative characterisation of the difference in comprehension between novices and experts working with simulations is necessary.

When taking into account a constant over-all load induced by all three kinds of cognitive load, persons with high prior knowledge benefit from their cognitive schemata by decreasing the intrinsic cognitive load. Obviously the reduction of intrinsic cognitive load leads to an increase of the germane cognitive load for people with high prior knowledge. Finally, experts working with simulations with worked-out examples achieve better results in understanding although they suffered more cognitive load than experts working with simulations with problem tasks. The fact that the lowest cognitive load for people with high prior knowledge working with simulations did not induce the best understanding indicates two complementary mental models derived from two different presentations. The comprehension of persons with high prior knowledge is limited by the quantity of information and the quality of the visual learning material, although cognitive resources are available for further information.

PERSPECTIVE

The results of this study raise the question of whether dual coding is always necessary for learning complex systems. Our results suggest that the visual representation alone could be sufficient for learners with low prior knowledge to achieve understanding. In the case of learners with high prior knowledge, however, the exclusive use of visual representation limits the acquisition of knowledge. Here, the second code, i.e. the text, is necessary. To get further evidence concerning the quality of understanding and learning strategies in visual processing, we want to analyse protocols of thinking aloud. Furthermore, we want to align those categories with the categories of understanding deriving from text. Further research on this subject will contribute to a better understanding of the construction of mental models with regard to complex dynamic systems in the field of science education.

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