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Instructional Efficiency of Animation: Effects of Interactivity through Mental Reconstruction of Static Key Frames

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SUMMARY

This study used cognitive load theory to investigate whether an animation about the cardiovascular system can become a more effective educational tool by designing it with sensitivity to the capacity limitations of working memory. To manage the high extraneous cognitive load imposed by the need to process series of successive and transient information elements, a sequence of static key frames from the animation was presented to learners directly after the animation. Two interactive instructional conditions, which required learners either to construct or reconstruct the sequence of key frames, were compared to a non-interactive condition. It was hypothesised that the interactive activities would lead to more efficient transfer performance. The results confirmed the hypothesis, indicating that the interactive conditions required less mental effort to attain the same performance as the non-interactive condition. Instructional design implications for learning from animations are discussed. Copyright © 2007 John Wiley & Sons, Ltd.

Electronic learning environments that include visualisations such as animations show great promise for teaching students about the chains of events in dynamic systems. Understanding of these systems involves knowledge of their configuration, behaviour and function, which can either be communicated by multiple static or by dynamic visualisations. While dynamic visualisations provide *external* animations that a user can view to learn how a system works, static visualisations require a process of internal or *mental* animation for comprehension of the system. So, whereas learning from animations relies on the students' ability to perceive the temporal changes in the operation of a system, learning from static graphics relies on the ability to infer these temporal changes. Inferring temporal changes is believed to be a more demanding process than perceiving temporal changes (Hegarty, Kriz, & Kate, 2003).

However, although, animations seem theoretically and intuitively a better instructional format for representing change over time than static graphics, a recent review paper by Tversky, Morrison, and Betrancourt (2002) indicates that research comparing static

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graphics with animations has failed to establish this advantage. It seems probable that these inconclusive results were caused by the fact that so far there are hardly any adequate research-based accounts of how people cognitively process and learn from such resources (Chandler, 2004). Consequently, conventional instructional materials using animation are not necessarily designed with sensitivity to the processing limitations of working memory and therefore may interfere with the learning process. In this study we argue that the analysis of dynamic visualisations from a cognitive load perspective can reveal conditions under which they may be effective learning devices. Using cognitive load theory (CLT; Paas, Renkl, & Sweller, 2003; Sweller, 1988, 1999, 2004), we argue that animations can be useful educational tools provided that they are designed with sensitivity to the processing limitations of working memory and the learner's expertise.

CLT is concerned with the instructional control of the high cognitive load that is typically associated with the learning of complex cognitive tasks. The theory suggests that learning happens best under conditions that are aligned with human cognitive architecture. CLT distinguishes between different categories of cognitive load. First, intrinsic or task load, which is related to the complexity of the domain, and second, extrinsic or instructional load, which is determined by the manner in which the information is presented to learners. The load imposed by information and activities that hinder the learning process is called 'extraneous', whereas the load related to information and activities that foster the learning processes is called 'germane'. Intrinsic, extraneous and germane load are considered additive in that, taken together, the total load cannot exceed the memory resources available if learning is to be maximised (see Paas, Tuovinen, Tabbers, & Van Gerven, 2003).

Based on CLT, it can be argued that the critical characteristic of animation that is frequently overlooked when considering it for instructional use, is that it consists of a series of successive and transient elements. Important information, which was briefly present, disappears before it can be retained in long-term memory (LTM). Attempts to keep such information active in working memory (WM) while simultaneously receiving new information causes high extraneous cognitive load and is therefore a major detriment to learning from animations.

Several studies have tried to manage the high extraneous load imposed by the continuous flow of transient information elements with specific strategies such as segmenting, cueing and tracing (e.g. Betrancourt, 2005; Marcus, KhengJoo, Beng-Fei, & Ayres, 2006; Mayer & Chandler, 2001). The 'segmenting' method decreases extraneous load for novices by breaking down the animations into segments corresponding to meaningful parts of the demonstrated process (e.g. Mayer & Chandler, 2001). The 'cueing' method decreases extraneous load by providing cues that focus the learners' attention on the relevant parts of the animations (e.g. Betrancourt, 2005). The 'tracing' method decreases extraneous load by leaving a trace in which key information is kept available (Marcus et al., 2006). The tracing strategy keeps information available in a sequence of key frames, rather than having it replaced by the ongoing animation. By retaining information in a trace, the demands on WM are reduced: The learner has more time to process the information and commit it to LTM while reducing the likelihood of cognitive overload.

Decreasing extraneous load may be necessary to prevent cognitive overload, but, at least equally important, it frees up cognitive resources that can be used for cognitive processes that are directly relevant to learning. These schema-construction processes cause the so-called germane load (see Sweller, Van Merriënboer, & Paas, 1998). However, learners will not always engage in such activities spontaneously. Hence, cognitive load research has started to shift attention towards the identification of instructional techniques that stimulate learners to invest cognitive resources in activities relevant for learning, that is techniques that are successful at inducing germane cognitive load (Paas et al., 2003; Paas, Renkl, & Sweller, 2004; Sweller et al., 1998; Van Merriënboer & Sweller, 2005). Strategies that are known to increase germane cognitive load for novice learners studying worked examples, are, for instance, increasing variability of practice (e.g. Paas & Van Merriënboer, 1994), contextual interference (e.g. Van Merriënboer, Schuurman, De Croock, & Paas, 2002) and prompting students to self-explain the rationale behind worked-out solution steps (e.g. Atkinson, Renkl, & Merrill, 2003). Several recent studies found that increasing the level of interactivity of animations can be used as a way to increase germane cognitive load, as indicated by positive effects on recall and transfer performance (e.g. Bodemer, Ploetzner, Feuerlein, & Spada, 2004; Hegarty et al., 2003; Schnotz & Rasch, 2005). Such interaction may stimulate learners to invest more mental effort in meaningful learning activities (i.e. increase germane load.

This study investigated the effects of two interaction strategies on learning from an animation about the cardiovascular system. To manage the high extraneous cognitive load imposed by the need to process series of successive and transient information elements, a sequence of static key frames from the animation is presented to learners directly after the animation. The two interaction strategies that are expected to stimulate the development of schemas require learners either to mentally *reconstruct* a previous key frame or mentally *construct* a following key frame by extrapolating from a presented key frame of the animation. Adding interactivity to animations is believed to impose a germane load by stimulating learners to invest more mental effort in learning and enabling them to attain higher transfer performance. Mental construction and reconstruction of a sequence of static key frames of an animation is similar to so-called prediction assignments used by Hegarty et al. (2003; see also Byrne, Catrambone, & Stasko, 1999; Hegarty, Quilici, Narayanan, Holmquist, & Moreno, 1999). Construction and reconstruction of a sequence of key frames is believed to enhance learning from animation because it induces people to activate their acquired knowledge of the system and to enable people to verify their knowledge about the animation against the actual processes as presented by a sequence of key frames.

Cognitive load theory incorporates specific claims concerning the role of cognitive load within an instructional context and its relation to learning (for an overview, see Paas et al., 2003). Most importantly, it recognises that a meaningful interpretation of a certain level of cognitive load can only be given in the context of its associated performance level and vice versa. For instance, a performance score on a test does not provide any information about the cognitive costs at which this performance was attained. Therefore, taking both measures into account gives a better indication of the quality of the cognitive schemata participants have acquired than performance scores alone. This recognition has led Paas and Van Merriënboer (1993; see also Tuovinen & Paas, 2004) to develop a computational approach for examining the observed relation between measures of test performance and measures of mental effort invested in the test. This approach enables cognitive load theorists and instructional designers to calculate and compare the efficiency of instructional conditions: High task performance associated with low mental effort is termed high instructional efficiency, whereas low task performance with high mental effort is termed low instructional efficiency. The value of the approach has been proven by revealing differential effects of varying instructional methods that would have been unnoticed with conventional performance measures (e.g. Cuevas, Fiore, & Oser, 2002; Kalyuga, Chandler, & Sweller, 1998; Kalyuga, Chandler, Tuovinen, & Sweller, 2001; Paas & Van Merriënboer, 1994; Pollock, Chandler, & Sweller, 2002; Van Gerven, Paas, Van Merriënboer, Hendriks, & Schmidt, 2003; Van Merriënboer et al., 2002).

Consequently, it was hypothesised that by using a sequence of static key frames from the animation directly after the animation, the effects of transient information will be neutralised and there would be enough spare cognitive resources to be used for interactive activities imposing a germane cognitive load. More specifically, the two interactive traced instructional conditions requiring learners either to construct or reconstruct static key frames from the animation were expected to lead to a higher instructional efficiency than a non-interactive instructional condition (the control group). However, higher efficiency was only expected in terms of the original Paas and Van Merriënboer (1993) definition, which is indicative for germane cognitive load effects (see Paas & Van Gog, 2006).

METHOD

Participants

Participants were 85 psychology students (52 females and 33 males) of Maastricht University. Their average age was 20.6 years. They received €15 for their participation. Participants were randomly assigned to one of the three conditions in such a way that males and females were equally distributed across conditions. This resulted in 29 participants in the non-interactive condition, 28 participants in the interactive condition with a construction assignment and 28 participants in the interactive condition with a reconstruction assignment. Participants were tested in groups of 10 or less.

To control for differences in non-verbal intelligence, Raven's (1962) *Advanced Progressive Matrices* (APM) test was administered to the participants. This test asks participants to find the missing part required to complete a logical pattern. Scores did not differ across experimental groups (non-interactive: $M = 25.62$, $SD = 3.45$; interactive construction: $M = 25.64$, $SD = 3.93$; interactive reconstruction: $M = 25.57$, $SD = 3.32$), $F(2, 82) < 1.0$, ns.

Materials and procedure

The materials covered the functional anatomy of the cardiovascular system. The whole experiment was developed with Macromedia Flash Professional MX (2004) and presented on an IBM-compatible computer. Participants received general instruction providing procedural information about the experiment (self-paced timing), and took a pretest consisting of 22 multiple choice questions on structures and functions of the cardiovascular system (self-paced timing). Then the learning phase started. This phase consisted of the presentation of basic anatomical knowledge about the cardiovascular system (5 minutes, computer-controlled), and an animation about the working of the cardiovascular system (1 minute, computer-controlled). Subsequently, the condition-specific instruction of the three experimental conditions started and was computer-controlled and took 8 minutes for all groups.

In the *non-interactive condition*, participants were shown all seven diagrams of the cardiovascular system in different phases simultaneously. These seven diagrams were static key frames of the animation. Participants were asked to study these key frames. Examples of the interaction requirements are depicted in Figure 1. In the *interactive condition with construction assignment* (see top panels in Figure 1), participants were

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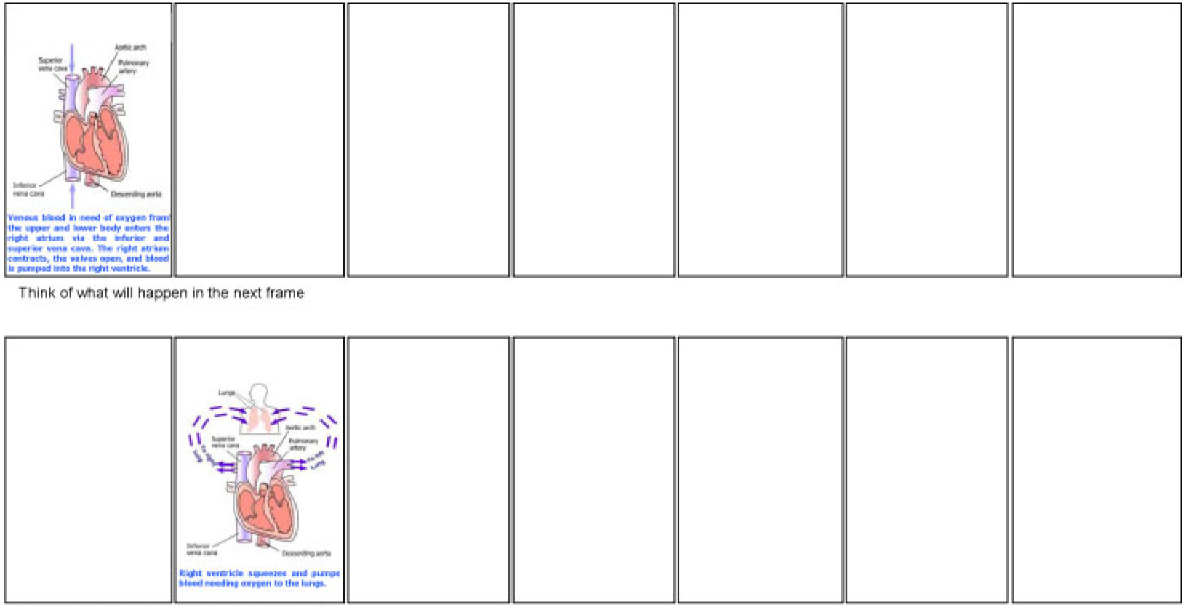

Think of what will happen in the next frame

Think of what happened in the previous frame

Figure 1. One of seven construction (top panels) or reconstruction (bottom panels) assignments of the interactive conditions

presented with the first of seven static key frames, which they had to study for 25 seconds. After that, they were asked to think for 25 seconds what would happen in the second key frame. Then the second key frame was shown and participants were asked to verify their ideas and to study this frame. Subsequently, they were asked to think what would happen in the next key frame. After 45 seconds, the third key frame was shown and they were asked to verify their ideas and study this frame for 25 seconds. This process was repeated until the seventh and last key frame was shown. In the *interactive condition with reconstruction assignment* (see bottom panels in Figure 1, participants were presented with the first of seven static key frames, which they had to study for 25 seconds. After that, the first key frame disappeared and the second key frame appeared. Participants were asked to think for 25 seconds what happened in the frame that disappeared. After that, the first frame appeared again and participants were asked to verify their ideas for 20 seconds. Next, the third key frame was presented, which they were required to study for 25 seconds. After that, the second frame disappeared and the participants were asked to think for 25 seconds what happened in the frame that disappeared. After that, the second frame appeared again and participants were asked to verify their ideas for 20 seconds. This procedure was repeated until the seventh and last key frame was shown. Finally, participants in all conditions took a posttest comprising the same 22 multiple choice questions as in the pretest, but in a different order. Although there was no maximum time to complete the pre- and posttest, participants were instructed to solve the problems as fast and accurate as possible.

Participants had to rate the amount of invested *mental effort* on a computerised version of the nine-point symmetrical category scale developed by Paas (1992; Paas & Van Merriënboer, 1994), by translating the perceived amount of mental effort into a numerical value. The numerical values and labels assigned to the categories ranged from very, very low mental effort (1) to very, very high mental effort (9). The scale was provided to the participants twice during the pretest (after half and after all of the questions), once after the condition-specific instruction and twice during the posttest (after half and after all of the questions). The two ratings on the pretest and on the posttest were averaged for the analyses conducted in the results section.

RESULTS

The data were analysed with one-way analyses of variance (ANOVAs). Dependent variables were time, transfer performance and perceived mental effort on the pretest, the condition-specific instruction and the transfer test. Furthermore, instructional efficiency was calculated using Paas and Van Merriënboer's (1993; Tuovinen & Paas, 2004) computational approach by standardizing each of the participants' scores for transfer performance and mental effort invested in the test. For this purpose, the grand mean was subtracted from each score and the result was divided by the overall standard deviation, which yielded z-scores for effort, R, and performance, P. Finally, an instructional efficiency score, E, was computed for each participant using the formula: $E = (P - R)/\sqrt{2}$.

In case of a significant F test, post-hoc multiple comparisons were conducted using Fisher's LSD procedure. The significance level for post-hoc tests was set at $p < 0.05$. For the ANOVAs, Cohen's f statistic was used as an effect size index, where f values of 0.02, 0.15 and 0.35 correspond to small, medium and large values, respectively (Cohen, 1988). Table 1 shows the means and standard deviations of the dependent variables as a function of instructional condition.

Table 1. Means and standard deviations (between brackets) of the dependent variables as a function of instructional condition

Dependent variable	Instructional condition		
	No interaction	Interaction: construction	Interaction: reconstruction
Pretest			
Time (seconds)	155 (60.7)	183 (60.1)	162 (45.6)
Mental Effort (1–9)	6.6 (2.39)	7.0 (1.68)	7.1 (1.83)
Performance (0–22)	11.2 (4.00)	11.3 (3.07)	10.7 (3.11)
Instruction			
Mental effort	3.6 (1.80)	2.8 (1.42)	2.2 (1.22)
Transfer test			
Time (seconds)	144 (38.8)	134 (30.4)	141 (41.9)
Mental effort (1–9)	3.2 (1.74)	2.4 (0.95)	2.2 (0.76)
Performance (0–22)	17.3 (2.62)	18.3 (1.66)	18.1 (2.05)

The results on the pretest indicated that the three conditions did not differ in prior knowledge. Participants spent the same amount of time, $F(2, 82) = 1.90$, $p = 0.156$ and mental effort, $F(2, 82) < 1.0$, ns and attained the same performance, $F(2, 82) < 1.0$, ns, on the pretest. Furthermore, the means for the pretest indicate that the students had some prior knowledge on the subject matter, but overall were not high in expertise, and therefore can be considered relative novices.

The invested amount of mental effort in the condition-specific instruction differed as a function of condition, $F(2, 82) = 6.28$, $MSE = 2.27$, $p = 0.003$. Cohen's f statistic for these data yielded an effect size estimate of 0.39, which corresponds to a large effect. Multiple comparisons showed that participants in the non-interactive condition invested more effort than participants in both interactive conditions, which did not mutually differ.

The ANOVA performed on the transfer test scores showed that there were neither significant effects of instructional condition on the total numbers of problems answered correctly, $F(2, 82) = 1.55$, $MSE = 4.64$, $p = 0.219$, nor on the time spent on solving the transfer problems, $F(2, 82) < 1.0$, ns. The invested amount of mental effort in solving the transfer problems differed as a function of condition, $F(2, 82) = 4.89$, $MSE = 1.52$, $p = 0.01$. Cohen's f statistic for these data yielded an effect size estimate of 0.35, which corresponds to a large effect. Multiple comparisons showed that participants in the non-interactive condition invested more effort than participants in both interactive conditions, which did not differ. The ANOVA performed on the instructional efficiency scores, which are depicted in Figure 2, differed across conditions, $F(2, 82) = 5.70$, $MSE = 0.95$, $p = 0.005$. Cohen's f statistic for these data yielded an effect size estimate of 0.37, which corresponds to a large effect. Multiple comparisons indicated that participants in the non-interactive condition had to invest more effort than participants in both interactive conditions to attain the same transfer performance.

DISCUSSION

In line with the main hypothesis, this study showed that the instructional efficiency was higher in the interactive animation conditions than in the non-interactive animation

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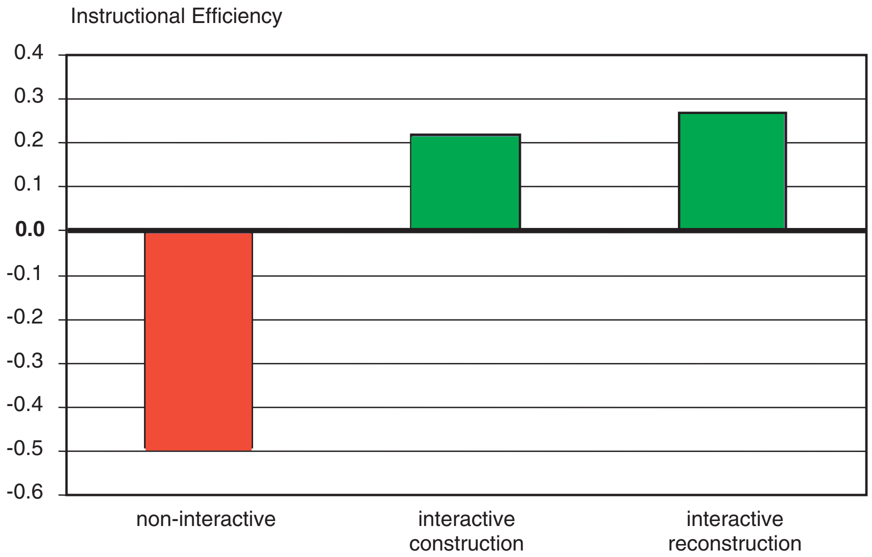

Figure 2. Instructional efficiency as a function of instructional condition

condition. Higher instructional efficiency was considered indicative for better schema construction. Moreover, the participants in the non-interactive condition not only invested more mental effort to attain the same transfer performance (i.e. lower instructional efficiency), they also invested more mental effort in the condition-specific instruction. This finding suggests that studying the animation with the sequence of static key frames in the non-interactive condition imposed a higher extraneous load than studying the animation with static key frames with a construction or reconstruction assignment in the interactive conditions. Apparently, the interactive conditions imposed a lower, but germane cognitive load, as reflected by higher instructional efficiency. The higher cognitive load in the instruction phase of the non-interactive condition might be explained by the fact that the participants were significantly affected by the simultaneous presentation of all static key frames. In the interactive conditions the static key frames were presented one by one. Since the key frames corresponded to meaningful parts of the demonstrated process, the present results might also have been caused by a kind of segmenting effect or a combination of such an effect with interactivity. Future research, therefore, should attempt to unravel these factors, for instance by comparing the interactive condition to a non-interactive condition in which key frames are presented one by one.

The results of this study can provide interesting information for educational practice in the sense that interactive activities using static key frames from the animation may increase the instructional efficiency of animations for novices. However, replication studies are needed to substantiate this claim. In the context of cognitive load theory, it would also be important for future research to investigate how task complexity and learner expertise affect the instructional efficiency of interactive activities with animations. For example with very complex tasks, learners might experience such a high intrinsic cognitive load that adding germane load in any form does not make sense, even after removal of all extraneous load. In these circumstances it may be necessary to reduce intrinsic load by isolating

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interacting elements (see Ayres, 2006; Pollock et al., 2002) or by other strategies common in complex domains (e.g. Van Merriënboer, Kester, & Paas, 2006).

With regard to learner expertise and the expertise reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003), it would be interesting to compare the present results with those found in studies on the 'imagination effect' (e.g. Cooper, Tindall-Ford, Chandler, & Sweller, 2001; Leahy & Sweller, 2005). The expertise reversal effect occurs when instructional procedures that are effective for novices become ineffective with increased expertise in the domain of interest. The imagination effect is obtained when learners asked to imagine a procedure learn more than learners simply asked to study the same procedure. Characteristically, this effect is only obtainable with more knowledgeable learners and not with complete novices. Because the interactive strategies that were used in this study can be argued to resemble imagination strategies, our results with relative novices, can be considered rather surprising. The fact that the interactive mental construction and reconstruction of static key frames of the animation was superior to just studying all the static key frames of the animation might be due to the fact that in this study participants had to mentally (re)construct only small parts (i.e. key frames) of one worked-out animated example. In the Cooper et al. study, participants had to imagine a procedure for a whole worked-out example. Asking participants to (re)construct a small part of an animation might have simplified the problem in such a way that enough cognitive resources were left to profit from the interactive activities. Future research could investigate this hypothesis.

In summary, this study suggests that adding interactivity by asking learners to construct or reconstruct static key frames from an animation seems to be a promising instructional strategy to improve learning from animations.

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