

Dynamic Media in Computer Science Education; Content Complexity and Learning Performance: Is Less More?

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ABSTRACT

With the increasing use of dynamic media in multimedia learning material, it is important to consider not only the technological but also the cognitive aspects of its application. A large amount of previous research does not provide preference to either static or dynamic media for educational purposes and a considerable number of studies found positive, negative or even no effects of dynamic media on learning performance. Consequently, it is still necessary to discern which factors contribute to the success or failure of static or dynamic media. The study presented here can be seen as another brick in the wall of understanding students' learning supported by dynamic media. In this study, aspects of cognitive load and the ability to generate mental representations for the purpose of appropriate animation design and development are considered. The learning performance of static versus dynamic media amongst a total of 129 Computer Science students, including a control group, was investigated. The results showed that learning performance using dynamic media was significantly higher than those of the static textbook lesson when the learning material had a certain level of complexity; the more complex the learning material, the larger the benefit of using animations. The results were examined for possible factors that contributed to the success or failure of dynamic media in education. In conclusion, this study has successfully confirmed the theory that dynamic media can support learning when cognitive load and learners' mental representations are taken into account during the design and development of learning material containing dynamic media.

Keywords

Static media, Dynamic media, Animations, Learning performance, Cognitive load

Introduction and Motivation for Research

A common distinction of learning material refers to static (e.g., texts or images) and dynamic (e.g., animations or simulations) media. Dynamic media are very popular and are almost omnipresent in today's information and media society. Dynamic media, moreover, is an increasingly important factor in educating the so called *twitch speed generation*.

The term *twitch speed generation* was introduced by Prensky (2001) and basically means the under-30 generation, whom he presumes to be capable of processing information *faster* and more *in parallel* than the generations before. Prensky sees some reasons for this change in information processing in the increasing influence on children and adolescents of speeding media such as MTV (music television) or computer games.

While initiated by such manifest considerations, the following research also resulted from a practical question: The publisher (Vogel Wuerzburg, Germany) of the first author's student textbooks (Holzinger, 2002) for computer science students wanted to know, whether offering additional electronic material in the form of small multimedia Learning Objects (LO) with these textbooks would benefit the students and, if so, to what extent. Naturally, the cost/benefit ratio of such electronic learning material is also an issue for a publisher. However, in this study we concentrate on aspects of learning performance of generic learning material, although we investigated the technological aspects of such Learning Objects, their interoperability, reusability, and packaging on learning platforms (see e.g. Holzinger, Nischelwitzer & Kickmeier-Rust (2006)).

Consequently, three main questions emerged: 1) Is there, principally, a discernable difference in learning performance between electronic learning material, shown here in the form of minimal (“spartanic”) electronic learning material (containing dynamic media), and printed matter (static media, including diagrams and pictures); and 2) if there is a difference, what are these differences and how far do they extend? Finally, 3) what can we learn from research, which can be applied to the design and development of such multimedia learning material? From this, one can conclude the necessity of combining research in Human–Computer interaction (HCI), which delivers the necessary findings, with Usability Engineering (UE), which ensures the appropriate practical application of the results in development at systemic level (Holzinger, 2005).

A survey of the literature failed to provide clear guidelines as to which types of animations are suitable for which information. Moreover, past research relied primarily on certain standard type animations (e.g., on how lightning works, how a toilet tank works, or how brakes work etc.) and most of the experiments took place in a laboratory setting (cf. Mayer, 2005), rather than in real world environments. In our opinion, contributing to the investigation of these questions, research must be more *context-orientated* and both the psychological and developmental aspects must be taken into account (Holzinger & Ebner, 2003, 2005).

Past Research

A considerable part of past research on the impact of different types of media on learning performance is based on the simple distinction in dynamic and static media. Dynamic media can be divided into *interactive* (e.g., computer simulation within which the learner can manipulate certain variables) and *non-interactive* media (e.g., animations or movies). Ainsworth & van Labeke (2004) argued that the classification as either static or dynamic representation is probably an insufficient level of granularity. A more detailed classification refers to aspects such as *modality* (text or images), *abstraction level* (for example iconic or symbolic), *sensory channel* (auditory or visual), *dimension* (i.e., 2D or 3D), and *dynamism* (static media versus dynamic media). Lowe (2004), additionally, identified three characteristics of animations, *transformations* (which alter properties of objects such as size, shape and color), *translations* (which move objects from one location to another), and *transitions* (which make objects disappear or appear). Besides static representations, Ainsworth & van Labeke (2004), proposed three types of dynamic representations.

The first type is a *Time Persistent Representation (TPR)*, which is similar to static media; the only difference between a representation within a textbook and an animation is that the dynamic representation displays information incrementally rather than presenting the whole information from the beginning. Taking, for example, a time-series graph and making it dynamic does not add any new information, although it may make certain features of that information more pronounced.

The second type is *Time Implicit Representation (TIR)*, which shows the relationship between variables over a period of time. Unlike the TPR, the timescale of this information is *only perceivable when presented dynamically*. The rate of change of the values being graphed is only visible when the animation is running and the representation is being adjusted dynamically. Consequently, when a simulation is stopped, viewers must invoke internal representations to compare current values to a particular previous state in order to answer questions about the timeline.

The third type, *Time Singular Representation (TSR)*, displays one or more variables at a single instance of time. This is the classical case of animation which is transitory. As TSRs display one state of the system, they contain less information for each dimension of information in comparison to TPR and TIR. As a result, they are often used when the information to be conveyed is highly *complex* and involves many interacting elements. Consequently, when an animation does not move, the external representation contains only limited information, *placing higher demands on cognitive ability*. For example, to compare current values to previous ones, viewers must hold previous states in their memory in order to integrate them with new information; such activities are known to place much effort on working memory (Hagafors & Brehmer, 1980).

Research on the impact of dynamic and static media on learning performance has a long tradition and is consequently rich in empirical results. Generally, past research revealed that the mode of presenting learning contents significantly affects learning processes and, therefore, learning performance (cf. Mayer, 2001). Often it was assumed that dynamic media might be the most successful method for presenting learning content about complex

dynamic systems and that such dynamic media might significantly facilitate learning (e.g., Davies, 2002; Park & Gittelman, 1992).

Past research, however, found little support for this assumption and research results showed that learning with static media is equal or even superior to learning with dynamic media (cf. Mayer, Hegarty, Mayer, & Campbell, 2005; Tversky, Morrison, & Betrancourt, 2002). For example, Mayer et al. (2005), reported that in a series of experiments, learning with static media resulted in significantly higher, or at least equal, learning performance than with animations.

On the basis of these results, one needs to consider the *advisability* of using dynamic media for displaying information and for educational purposes. Past researchers, however, also argued that dynamic media might be superior to static media for learners with low spatial abilities or with *increasing complexity of learning content*. Furthermore, Narayanan & Hegarty (2002) argued that dynamic media might be superior when the learning content deals with processes, which are not observable in the real world (in computer science, for example, computer algorithms). The question as to which types of animations are suitable in which situations; for which contents and for which learners still remains a matter of debate.

Theoretical Background

As mentioned above, previous research provided inconsistent and sometimes contradictory results on effects of different types of media and their learning performance. A number of studies found dynamic media advantageous (e.g., Kaiser, Proffitt, Whelan, & Hecht, 1992; Rieber, 1991), other studies found disadvantages in dynamic media (e.g., Mayer et al., 2005; Rieber, 1990; Schnotz, Böckheler, & Grzondziel, 1999) and often *no* differences in learning performance were found (e.g., Mayer et al., 2005; Price, 2002; Pane, Corbett, & John, 1996).

According to Ainsworth & van Labeke (2004), research on dynamic media effectiveness has produced those mixed results for a variety of reasons: First, methods and measures used to investigate the impact of different types of media varied (cf. also with Price, 2002); second, the types of animation used for research were mostly the same (as mentioned within the introduction), and third, learners' individual differences may contribute to different learning performance with different media. For example, some learners tend to focus on the more obvious perceptual events rather than on those that are of most conceptual interest.

Lowe (2003) argued that processing dynamic media may be problematic in two ways. First, learners may tend to view animations only superficially and under-process them due to a lack of cognitive challenge or engagement.

Second, learners may be intensively occupied with animations, however, they may be unable to process the presented material satisfactorily due to an excessive cognitive challenge or cognitive demands imposed. This excessive strain is associated with aspects of animations such as high *information load* (particularly if the subject matter is complex) and the temporally distributed nature of the presentation. Consequently, the different information (e.g., graphical elements) may cause split-attention effects, that is, an *increase of extraneous load* when presenting related information spatially or temporarily separated. Such effects have been investigated, for example, between pictures and text (cf. Mayer & Moreno, 1998).

Ferguson & Hegarty (1995) characterize static diagrams as often being underspecified, a characteristic that can result in problems for learners in the proper compartmentalization of the display into appropriate graphic elements (*features*). Animations present the additional challenge of dividing the temporal sequence into events involving features in the display that are thematically relevant (*feature events*). Moreover, in traditional animation, the material is presented in a predetermined manner that plays from start to finish without the possibility of viewer control over such aspects as the length of the animated sequence viewed; its pace and its direction. However, learners could be at a disadvantage if their speed of comprehension cannot keep pace with the speed at which an animation presents its information (Hegarty, Narayanan, & Freitas, 2002).

A further reason for inconsistent results may lie in the research methods. Often static media and dynamic media did not display the same information or the same amount of information, dynamic media images were superior to those of their static counterparts, maximum learning effects were reached and, in some cases, the dynamic media learning

procedures were superior to those of the static media (cf. Betrancourt & Tversky; 2000; Hegarty, Kriz, & Cate, 2003; Lowe, 1999; Mayer et al., 2005; Tversky, Morrison, & Betrancourt, 2002). Even in cases where static media and dynamic media are comparable both in content and visually, it does not necessarily follow that dynamic media is superior to static media in terms of perceptual or cognitive demands. From a theoretical perspective, the most prominent theoretical frameworks for explaining the effects of different learning modalities are the *Theory of Multimedia Learning* (Mayer, 2001, 2005) and the *Cognitive Load Theory* (Paas, Renkl, & Sweller, 2003; Sweller, 1988, 1999, 2005; Valcke, 2002).

Mayer's theory is based on three assumptions: First, it is assumed that visual and auditory information is processed via different information channels. This assumption goes originally back to ideas of the *Dual Coding Theory* (Clark & Paivio, 1991; Paivio, 1991; Paivio & Csapo, 1973) which states that human working memory consists of two separate but *interrelated channels* for processing information: verbal channel and pictorial channel. Whilst these channels can be activated independently, there are interconnections between the two systems allowing *dual*, and therefore more efficient, coding of information (Rieber, 1994). The second assumption of Mayer's theory is that the processing capacity of each channel is *limited*. Only a small portion of information can be processed at one time. Finally, the third assumption interprets learning as an *active process*, for example by constructing *mental representations* of learning material and integrating it into existing previous knowledge (Holzinger, 2000).

Cognitive Load Theory (CLT) basically states that a learner's *attention* and working memory is limited. This limited amount of attention can be directed towards intrinsic, germane, or extraneous processing. *Intrinsic* processing describes a learner's focus on the learning content and its key features; it is determined by the intellectual demands of learning content (the complexity of the content). *Germane* processing describes a deeper processing of the content by its organization to cognitive representations and its integration into existing representations (integrating previous knowledge). Finally, *extraneous* processing describes cognitive demands during learning, which do not foster the actual objectives of the learning material, for example cross-references or navigation elements.

The problem with Cognitive Load Theory is, that it is rather difficult to quantify *cognitive load* of different representations or events. However, on the basis of this theoretical framework, Mayer (2001) defined his *static* and *dynamic media hypotheses*.

In brief, the static media hypothesis assumes that static media such as text or images facilitate learning processes by shifting attention and processing capacities from extraneous processing to germane processing by *providing only relevant information* (e.g., only important steps of a dynamic process) and by encouraging learners to *construct mental representations* of the learning material. Moreover, static media allow learners to control the pace and order of attended learning content. The dynamic media hypothesis, on the other hand, assumes that dynamic media such as animations might facilitate learning by reducing extraneous load and encouraging germane processing by reducing the efforts of constructing mental representations and by *attracting interest* and *increasing motivation*.

The Study

Initiated by our questions (see introduction) and on the basis of the inconsistent results of previous research (see theoretical background) and with regard to the influence of static and (non-interactive) dynamic media on learning performance, we compared the learning performance of a static textbook lesson (including static images), with the learning performance of animations on a very basic level. The aim of our study was primarily to identify factors that make dynamic representations of learning material beneficial for learning and to gain insight and gather knowledge for design and development of such learning material. We used small textbook lessons and developed corresponding animations, in order to provide a maximum of comparability between both representations and an isolated and controlled variation of experimental variables. Moreover, we realized three different levels of complexity of learning material.

Based on previous research we assumed that animations providing equal or lower cognitive load, dynamic media are superior to static media. Measuring cognitive load, as mentioned before, is difficult. Therefore, we attempted to operationalize the cognitive load concept by the simplicity of learning material design.

We hypothesized that replacing static pictorial information, which can only be understood when reading the related text and constructing a mental representation of the concepts, with dynamic information representing a reasonable mental model of the concepts, leads to higher learning performance. Additionally, we assumed that the more complex the learning material is, the bigger is the advantage of learning with dynamic media in comparison to static media. To investigate these hypotheses, we realized a 3 x 3 factorial design with three experimental conditions (static media *S*, dynamic media *D*, and a control group *C*) and three levels of complexity (L1 – L3). The experiment was conducted in a real-life classroom scenario.

Participants

The participants of the present study were N=129 undergraduate students of Computer Science from both Graz and Vienna University of Technology. In total, there were 27 female and 102 male students. The average age was 21.60 years (SD = 2.14), the youngest participant was 18, the oldest 28 years of age. The first part of the participants (in total 49) was recruited during the winter term 2002/03 and the last part (in total 80) during summer term 2007.

Materials

For the experiments, we used a small and clearly limited amount of generic learning content. We selected a one-page textbook lesson (from Holzinger, 2002) on various topics in basic Information Technology, particularly we selected signal transmission, which explains the fundamental principles of simplex, semi-duplex, and duplex transmission of signals (Figure 1).

This example consisted of short, simply organized text paragraphs and three static images. This material also included three different levels of complexity (i.e., simplex – low complexity, duplex – medium complexity, semi-duplex – high complexity), whilst the general topic and the visual representation of these levels were the same.

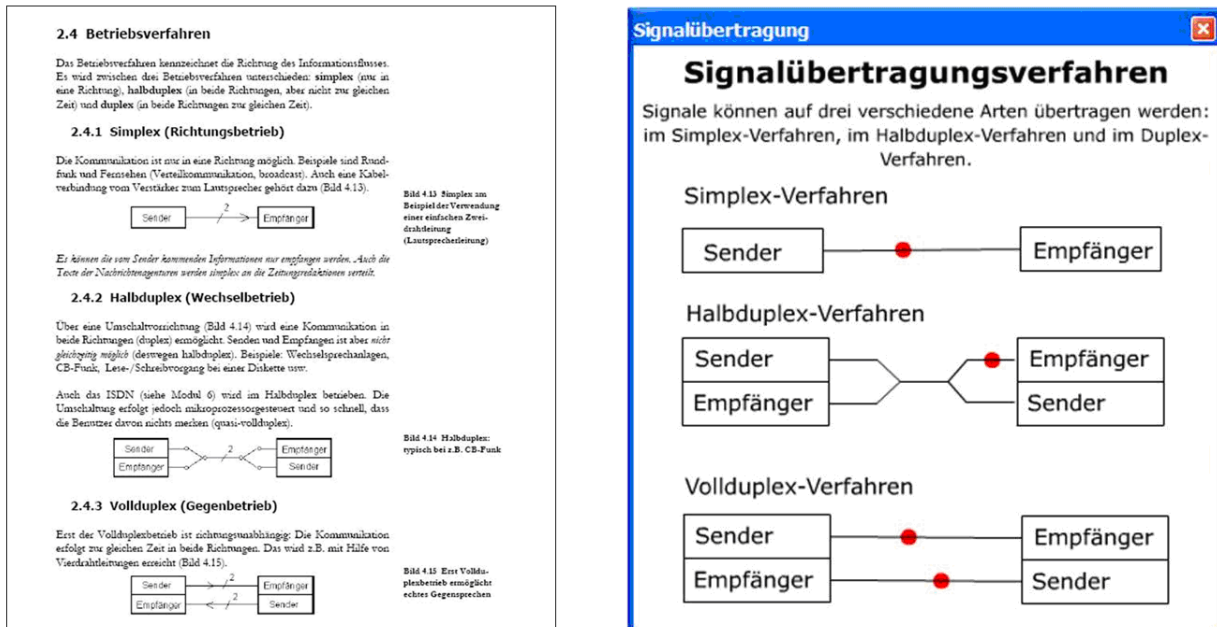


Figure 1. The left panel illustrates the static textbook lesson used in the present experiment. The right panel illustrates the corresponding dynamic representation

In addition we developed a time implicit animation (Ainsworth & van Labeke, 2004) using Macromedia Flash MX, representing exactly the same content. To realize animations that are as comparable as possible to the static textbook lesson we used the same terminology, the same information, and the same type of visualization. In the dynamic

representation we skipped only verbal and pictorial information (i.e., arrows in the static images) which directly referred to signal transmission paths and replaced it with animated dots displaying the transmission paths (Figure 1, right panel). The dots moved according the transmission direction at a pace of approximately 100 pixel per second and the animation was looped during the whole presentation. In contrast to a number of previous similar studies, we attempted to design the animation *with a maximum of simplicity*, meaning that we avoided designing appealing visual gadgets (e.g., transmitters etc.).

To assess *conceptual knowledge* in this particular domain and to record learning performance, we created a multiple choice test, which included three main topics, each assigned to each of the signal transmission modes. The three items were chosen in order to represent three different levels of complexity, high (L1), medium (L2), and low (L3). Each item had four answer alternatives, whereby none, one, or more alternatives could be correct. The score for each item ranged from 0 to 4 and the guessing probability for each item, consequently, was 6.25 percent. This test was used to assess previous knowledge in a pre-test and learning success in a post-test after the learning sessions. In the pre-test, we additionally asked for biographic data (for example age or sex) and we recorded a subjective rating regarding the participants' expertise in the domain of communication technologies and three ratings regarding learning preferences ("I like learning from textbooks", "I like learning from computer animations", and "I am rather a visual learner type").

All ratings were based on a five-category scale, ranging from "I absolutely agree" (1) to "I absolutely disagree" (5). This scale type is appropriate for students in Austria because it corresponds to school grades (where 1 is the best and 5 the worst grade).

Procedure

At first, the participants were informed about the aim of the study and asked to rate four questions about their experience in communication technologies and their learning preferences. In addition, the participants completed the pre-test in order to assess previous knowledge. In the following, the participants were randomly assigned to one of the three experimental conditions (static textbook lesson, dynamic animations, and control group).

Participants in the static image condition *S* were presented copies of the textbook paragraph (see Figure 1) taken from Holzinger (2002). Participants in the dynamic animation condition *D* were seated in front of Personal Computers (Standard IBM-PC's, 17" screen, 1280 x 1024 pixel) and presented the learning material, containing the Flash animations (Figure 1, right panel). The additional control group *C* received a one-page text on computer systems, which was irrelevant for the domain of signal transmission. The participants were instructed to learn as much as possible within a fixed time of eight minutes. The eight minutes interval was selected based on a pilot run with experts and students in order to determine an average benchmark time sufficient to go through the learning material. Moreover, this interval acknowledged real-life learning scenarios within which the time students can spend on learning content is most often limited. After a short break of 15 minutes (to make sure that students do not have the material in short term memory), all participants of the three experimental conditions were asked to complete the post-test in order to assess their learning performance. Finally, the participants were debriefed. The complete procedure took about 40 minutes.

Results

The main focus of the present study was learning performance with static (*S*) and dynamic (*D*) learning material. The learning performance of these groups, in addition, was compared with the results of the control group (*C*). As expected, in the pre-test scores no differences between the experimental conditions were found. In condition *S* participants achieved an average total score (i.e., the sum of scores in L1, L2, and L3) of 7.66 (SD = 2.07), in condition *D* a score of 7.34 (SD = 1.89), and in condition *C* a score of 6.86 (SD = 1.86).

As illustrated in Figure 2, equivalent results were found when the total score was divided into the three levels of complexity (Figure 2). The pre-test mean score in condition *S* was 2.02 (SD = 1.31) for L1, 2.59 (SD = .81) for L2, and 2.68 (SD = .76) for L3. In condition *D* the mean scores were 1.95 (SD = 1.08) for L1, 2.50 (SD = .88) for L2, and 2.70 (SD = .82) for L3. Finally in the control group *C* the mean scores were 2.02 (SD = 1.23) for L1, 2.25 (SD =

.92) for L2, and 2.59 (SD = .82) for L3. An analysis of variance (ANOVA) yielded non-significant differences between the levels of complexity L1 ($F(2, 128) = .047, p = .954$), L2 ($F(2, 128) = 1.729, p = .182$), and L3 ($F(2, 128) = .249, p = .780$). A post-hoc Scheffé test, moreover, revealed that no significant differences were found for the three experimental conditions (with p-values ranging from .210 to 1.000).

Confirming our initial hypotheses, in the post-tests different results were found. Condition *D* resulted in a higher average total score in the knowledge test (10.80, SD = 1.09) than condition *S* (9.39, SD = 1.56) and, in turn, condition *S* in a higher average total score than the control group *C* (6.95, SD = 1.76).

As illustrated in Figure 2, equivalent results were obtained for the three levels of complexity. For further analysis we computed the learning performance (i.e., the differences between post-test scores and pre-test scores for each level of complexity). In condition *S* the average learning performance was .85 (SD = 1.24) for L1, .54 (SD = 1.12) for L2, and .46 (SD = 1.16) for L3. In condition *D* the average learning performance was 1.68 (SD = 1.27) for L1, 1.05 (SD = 1.01) for L2, and 1.02 (SD = .95) for L3. Finally, in the control group *C* the average learning performance was .05 (SD = 1.29) for L1, .02 (SD = 1.15) for L2, and .02 (SD = .93) for L3.

An ANOVA yielded on the 5%-level significant differences in learning performance for all three levels of complexity (L1: $F(2, 126) = 18.321, p < .001$; L2: $F(2, 126) = 9.60, p < .001$; L3: $F(2, 126) = 10.70, p < .001$).

A post-hoc Scheffé test revealed significant differences between conditions *D* and *S* ($p = .013$), *D* and *C* ($p = .015$), and *S* and *C* ($p < .001$) for complexity level L1. For L2, significant differences were found between *S* and *C* ($p < .001$), however, not between *D* and *S* ($p = .105$) as well as *D* and *C* ($p = .101$). Finally for lowest level of complexity L3, significant differences were found between conditions *S* and *D* ($p = .044$) as well as *D* and *C*, between conditions *S* and *C* ($p = .140$) no significant differences were found.

Summarizing these results, the more complex the learning material was (and therefore the complexity of the test items), the larger were the advantages of learning with dynamic media (condition *D*) in comparison to condition *S*.

In the control group *C* no learning occurred (see Figure 2), as was expected. In order to verify the reliability of the test items, supposed to assess the conceptual knowledge in this particular domain of signal transmission, we computed Guttman's split-half coefficient for the test scores in the control group *C* in pre-test and post-test, which was .62 ($\alpha = 1.00$ in both parts). This result indicates a reasonable reliability of the test items.

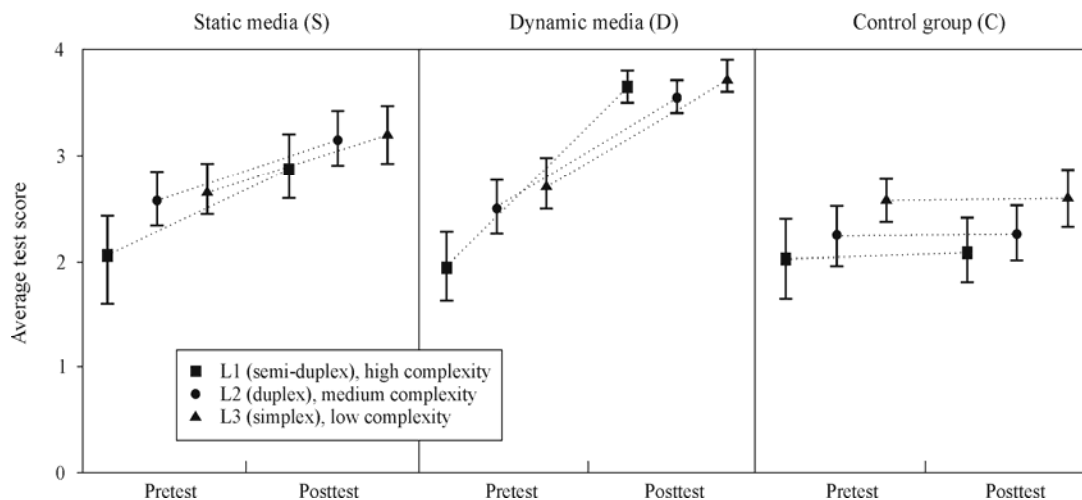


Figure 2. Mean test scores in pre-test and post-test for the three learning conditions (*S*, *D*, *C*) and three levels of complexity (L1 – L3). The whiskers indicate the 95% confidence intervals of the means.

Besides the knowledge tests, the participants were required to rate the following four questions on a scale from 1 to 5 (where a rating of 1 means complete agreement and 5 means complete disagreement):

Question Q1 referred to the participants' experience in communication technologies. The average rating was 2.75 (SD = 0.97).

Question Q2 referred to preferences for learning with static textbook lessons. The average rating was 2.78 (SD = 1.08).

Question Q3 referred to preferences for learning with multi-media material. Here the average rating was 2.70 (SD = 1.18).

Question Q4 referred to visual learning preferences. Here, the average rating was 2.29 (SD = .95).

Figure 3 illustrates the median (bold line), the range between 25th and 75th percentile (grey boxes), and minimum and maximum ratings (whiskers) for each question.

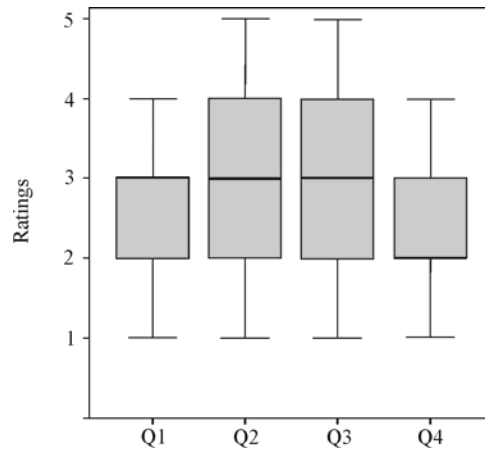


Figure 3. Box plots of the ratings in the four questions regarding experience in communication technologies (Q1) and preferences for static (Q2) and dynamic (Q3) learning material as well as regarding visual input preferences (Q4)

To analyze the relationships between the answers in these questions and test scores, we computed the Spearman correlations between the ratings and the total learning performance. As summarized in Table 1, we found only small to moderate correlations throughout; distinct correlations were significant on the 5% and the 1% level. These correlations demonstrated that the ratings in the four questions are confounded to a certain extent. However, the ratings in the four questions only moderately affected learning performance; higher experience in communication technologies (a lower rating) resulted – quite consistently – in higher learning performance and higher preferences for multi-media learning material (a lower rating) resulted in higher learning performance.

Table 1. Correlations between ratings in the questions regarding experience and preferences (Q1 – Q4) and learning performance

	Q1	Q2	Q3	Q4	Learning Performance
Q1	1	-.022	.0125	.266**	-.241**
Q2	-.022	1	-.338**	-.099	.057
Q3	.125	-.338**	1	.330**	-.191*
Q4	.266**	-.099	.330**	1	-.062
Learning Performance	-.241**	.057	-.191*	-.062	1

* Significant on the 5% level, ** significant on the 1% level

Discussion

Of course this study can only be a small part of a series of work aiming at finding another brick in the wall of understanding human learning supported by dynamic media. Our goal was to identify factors (in the present study we focused on *simplicity of design* and the *complexity of learning material*) that contribute to learning benefits through

dynamic media in order to gain insight on what to consider when designing and develop learning material including such dynamic media.

However, a large number of studies reported that learning with dynamic representations does not improve learning success per se; a few, contradictory, results were found which did not favor either static or dynamic media (cf. Betrancourt & Tversky, 2000; Hegarty, et al., 2003; Lowe, 1999; Mayer et al., 2005; Tversky, et al., 2002). Within our study, we focused on the *isolated variation of content complexity* and on *reducing cognitive load with simple animations*. We hypothesized that when animations provide more simplicity in design (and consequently lower cognitive load) they are superior to static media in terms of learning performance. Additionally, we assumed that the more complex learning material the larger the difference in learning performance between static and dynamic media. The results of our experiment provide some evidence for these assumptions.

In the present study, we found a considerable amount of previous knowledge in the relevant domain of Information Technology (i.e., signal transmission). Across the three levels of complexity, performance in the pre-tests was above 50% (i.e., above a score of 2 in each multiple choice item). This performance is clearly above the guessing probability. As shown in Figure 2, although a limited time interval was provided for learning and although participants had a relatively high level of previous knowledge, both experimental conditions (*S* and *D*) resulted in a *significant gain of conceptual knowledge*. Moreover, the present results confirm our assumptions about the impact of static and dynamic media on learning. While, as expected, no differences were found in previous knowledge on the topic of signal transmission in the pre-tests, the post-tests showed that animations resulted in significantly higher learning performance than the static textbook lesson. The differences in learning performance increased with an increasing level of complexity (Figure 2).

These results indicate that the complexity of learning material is an important factor for the success of learning material containing dynamic media. The more complex the learning content, the higher the benefits of using animations may be expected to be. This effect can be explained with the Cognitive Load Theory: In the case of simple content, only little efforts have to be spent on intrinsic and germane processing and, therefore, a certain amount of limited cognitive resources are available to process the verbal and/or visual representation of the content (i.e., extraneous processing). However, with increasing intrinsic load, the available resources for extraneous processing decrease and, consequently, the *importance of appropriate representations increase*. These results also provide some further evidence for the assumptions of the Dynamic Media Hypotheses. Mayer (2001) argued that dynamic media might facilitate the generation of mental representations of a process or a system and, additionally, might attract a learner's attention and interest. The animations developed for the present experiment offered a representation of signal transmission modes which likely corresponds to a meaningful mental model of that processes, because the animated dots display the continuous movement of a piece of information (a bit) from a sender to a receiver.

However, what factors in the present experiment made the animations the more appropriate form of representation? We argue that this, again, can be explained on the basis of Cognitive Load Theory. On the one hand, animated sequences require more extraneous processing because, instead of a single image, a time-frame of a series of individual images has to be perceived and processed. On the other hand, in the present experiment, we reduced cognitive load by avoiding text paragraphs explaining signal transmission paths, which is probably more demanding than just processing the animations of transmission directions.

Moreover, dynamic media are only appropriate and facilitate learning *when they represent a meaningful mental model* of a process or a system. This representation must also be within the limits of the cognitive system, and it must build upon *learners' previous knowledge and expertise*.

One argument for the inconsistent results regarding static versus dynamic media was individual differences (see for example Ainsworth & van Labeke, 2004; Price, 2002). In the present experiment we did not find indications for such assumptions. As shown in Table 1, only small correlations were found between individual experience, preferences for static or dynamic material, or visual input preferences and learning performance. Although the present work has a limited scope and focuses on a specific domain and a specific form of representation, we are of the opinion that our results and conclusions can be generalized.

Nonetheless, future research must extend beyond the limitations of this study, for example: the isolated and controlled investigation of different types of animations and the complexity of content must be investigated. An interesting issue for further research concerns the variations of the visualization complexity of a certain concept; also, it will be necessary to provide designers and developers of multimedia learning material with *rapid methods* to check – from the viewpoint of psychology – whether and to what extent, *their material is appropriately designed for the target end-users*. This means that per se Psychology and Informatics must closely cooperate in order to integrate findings from research into development at systemic level. Further work must also address interactive dynamic media (e.g., interactive simulations) to find out whether interactivity increases the complexity of the representation of learning material.

Conclusion

Although dynamic media and multiple media have become very present and popular in education, the existing community of research in this domain recommends a cautious use of such media (Mayer et al., 2005; Rieber, 1990; Schnotz, Böckheler, & Grzondziel, 1999). Dynamic media is only successful in facilitating learning in comparison to traditional static media such as texts or images, when they are able to (1) reduce the cognitive load, which is necessary to comprehend them, (2) serve to generate mental models of a concept and, consequently (3), offer visualizations that *correspond to a meaningful mental model*.

Moreover, dynamic media must be attuned to learners' experience, expertise, and most of all previous knowledge. Therefore, material containing dynamic media must avoid information, animations, and elements, which are *not necessary to comprehend a concept*. As an example, the signal transmission visualization, as in the present experiment, could have been made far more complex by using appealing graphics, more attractive signal representations, or more appealing background images, colors etc. Such information, however, *does not serve the comprehension* and the learning process and, not necessarily, the generation of *appropriate mental models*. The more complex and difficult the learning content is, the more important it is to direct cognitive and perceptual resources to intrinsic and germane processing. Finally, this study has successfully confirmed the theory that dynamic media *can* support learning when limited cognitive resources, cognitive load, and learners' mental representations are taken into account during the design and development of learning material containing dynamic media.

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