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Instructional advice, time advice and learning questions in computer simulations

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Undergraduate students (N = 97) used an introductory text and a computer simulation to learn fundamental concepts about statistical analyses (e.g., analysis of variance, regression analysis and General Linear Model). Each learner was randomly assigned to one cell of a 2 (with or without instructional advice) x 2 (with or without time advice) x 2 (with or without learning questions) between subjects factorial design. Time spent with the simulation as well as retention and transfer tests were used as dependent measures. Neither the instructional advice to examine the different parameters in a simulation systematically presented immediately before the simulation nor the learning questions (without feedback) presented during the simulation improves learners' retention or transfer performances. Students who were asked to employ more time on the computer simulation immediately before they want to finish it spent considerably more time with the simulation and performed better on retention, but not on transfer than did students for whom this request was absent. The results were discussed on the basis of the extended *Scientific Discovery as Dual Search* model and in conjunction with adaptive computer simulations.

Introduction

How can computer simulations be designed to optimise their instructional effectiveness? Computer simulations can be defined as programs where the user can perform experiments in controlled settings to understand how the underlying model of the simulation works (cf. de Jong & van Joolingen, 1998; van der Meij, 2007). These computer simulations typically have an underlying mathematical model programmed into them that dictates how the simulation behaves (Rieber, 2005). For example, a simulation that serves to understand the relationship between velocity and acceleration should be based on Newton's laws of motion. Learners can explore this underlying model by manipulating values of (input) variables and observing the behavior of other (output) variables (de Jong, 2006). These simulations become increasingly important in multimedia learning because they can be developed easily and are cost-efficient due to hardware and software improvements in recent years. However, simple implementation of computer simulations does not imply that learning effectiveness will be improved (de Jong, 2006). The purpose of the present experiment was to investigate how computer simulations and instructional advice should be designed to optimise their instructional effectiveness.

The following section presents (a) the extended *Scientific Discovery as Dual Search* (SDDS) model as well as (b) problems resulting from learning with computer simulations and (c) potential solutions to overcome these challenges. An experiment is followed up to test three different solution approaches as well as a discussion containing theoretical and practical implications, limitations and future research directions.

The extended *Scientific Discovery as Dual Search* (SDDS) model

There are different general theories that can be applied in the context of learning with computer simulations like the dual-coding theory (Paivio, 1986), the cognitive load theory (Sweller, 2005) or the cognitive theory of multimedia learning (Mayer, 2005a). The extended SDDS model developed by van Joolingen and de Jong (1997) is a more specific theoretical approach often applied in the context of learning with computer simulations. The model is an extension of Klahr and Dunbar's model of *Scientific Discovery as Dual Search* (SDDS) model (1988). In this model, learning with computer simulations can be described as a search process through two distinct but related problem spaces: the hypothesis space and the experiment space. The hypothesis space is the search space that contains all rules describing the phenomena that can be observed within the domain (universal hypothesis space) and also all rules a student can generate about a domain (learner hypothesis space). The experiment space consists of all experiments that can be performed within the domain.

The extended model from van Joolingen and de Jong (1997) provides a detailed elaboration of these two structures, for example it introduces diverse regions in the hypothesis space. In this model (as well as in the previous one) three basic processes are distinguished, which proceed in iterative cycles. First, "search hypothesis space" means that learners are searching the hypothesis space to generate a fully specified and testable hypothesis. Second, "test hypothesis" refers to the generation of a prediction, testing this prediction in the experiment space as well as the collecting of evidence. Finally, "evaluate evidence" is a process where the learner evaluates the collected evidence to verify or refine the hypothesis. A detailed taxonomy (e.g. generalisation or specialisation of a hypothesis, adding or removing a hypothesis from the hypotheses set, etc.) elaborates the search operations in hypothesis space (van Joolingen & de Jong, 1997).

Problems resulting from learning with computer simulations

Research indicates that many learners have substantial problems performing the three basic processes postulated in the SDDS model while using simulations (cf. de Jong, 2006; de Jong & van Joolingen, 1998). For instance, Dunbar (1993) showed, in a simulation environment, that some students have a strong inclination to search for evidence that supports their current hypothesis, and that this inclination may prevent them from stating an alternative hypothesis, even when they are confronted with contradictory evidence. In a study from Eysink, Dijkstra and Kuper (2001) students experimented with a simulation designed for teaching first-order logic in a way that they were confronted with subject matter they already understood, but without confronting themselves with less familiar situations. Keselman (2003) demonstrated that learners varied too many variables at one time in a computer simulation about the multivariable risks of earthquakes. Furthermore, learners fail to make predictions and make mistakes when interpreting data derived from the output of the simulation (Lewis, Stern & Linn, 1993). In summary, there are several empirical findings showing that learners often have serious problems learning adequately with computer simulations.

Potential solutions to overcome these problems

There are different approaches to alleviate the aforementioned problems, guide learners in using computer simulations, and improve learning with these simulations. For example, assignments (i.e., exercises that set the simulation in the appropriate state), explanations and background information as well as monitoring tools and hypotheses scratchpads can be used to produce effective and efficient learning situations (de Jong, 2006). Consecutively, three different possible solutions leading to three hypotheses will be discussed in detail.

First, adding instructional advice in computer simulations could overcome the problem that learners often do not learn adequately with simulations. This approach is consistent with findings from other researchers showing that instructional advice, annotations, scaffolding or other instructional support (collectively called guidance) can enhance learning efficiency (cf. de Jong, 2006; Mayer, 2004). For example, Eysink, Dijkstra and Kuper (2002) showed that interactive elements in a simulation designed for teaching first-order logic only increased learning outcomes if instructional advice which served to encourage learners to use these elements was added. In an earlier study (Rivers & Vockell, 1987) biology students worked with a computer simulation. Adding experimentation hints like "It is wise to vary only one variable at a time" before using the simulation did not influence learning outcome, but it had an effect on the students' experimentation abilities. In another study (Lin & Lehman, 1999) biology students used a computer simulation as well. Students who received prompts on experimental strategies outperformed those who received other prompts or no prompts at all on measures of far transfer (i.e., the ability to solve contextually dissimilar problems). Furthermore, Keselman (2003) found positive effects of an instruction in making predictions in a computer simulation about the multivariable risks of earthquakes.

Clarebout and Elen (2009) used advice on different tools and what the tools' functions were in a computer-based learning environment concerning obesity. Students receiving advice used the tools more frequently and spent more time on their use. However, the advice did not improve their learning results. Rey (in press) conducted two experiments, in which students had to work with a computer simulation about self-organising maps (i.e., a special kind of artificial neural network). In the first experiment, learners who received a reset button, which served to reset a visualisation to its initial state and enabled a more systematic exploration, did not perform better on succeeding retention or transfer tests than learners who did not receive a reset button. In the second study, instructional advice ("Use the reset button primarily to check the different parameters systematically") was added before the simulation. Students who received that advice used the button more often and performed better on transfer than students not receiving that advice.

In summary, there are several empirical findings showing that adding instructional advice or other instructional support can improve learning in computer simulations. It is expected that adding instructional advice can contribute to improve the three basic processes postulated in the SDDS model (i.e., search hypothesis space, test hypothesis and evaluate evidence). More precisely, it is assumed that adding instructional advice can eliminate a possible production deficit (i.e., learners possess the required strategies for exploring the simulation systematically, but do not use these strategies spontaneously) in regard to exploring the simulation systematically (i.e. generating and testing hypotheses about different parameter settings, cf. SDDS model). Therefore, the first hypothesis predicts that students who are advised to examine the different parameters in a simulation systematically before using the simulation perform better on retention and transfer than do students for whom this advice is absent.

Second, adding time advice in computer simulations could improve students' learning outcomes while learning with simulations. This approach is atypical to current methods postulated from other researchers which tried to improve the handling with the simulation (e.g., de Jong, 2006), but did not try to extend time spent with the simulation. Furthermore, it could be assumed that adding instructional advice on how to use the simulation could foster learning outcomes at least partly, by increasing the time spent with the computer simulation. In that case, only encouraging students to spend more time with the simulation should also improve learning outcome (e.g., by repeating the instructional material). Moreover, it could also be assumed that adding time advice can eliminate a possible production deficit (see above) in regard to exploring the simulation systematically (i.e. generating and testing hypotheses about different parameter settings, cf. SDDS model) due to perceived time restrictions of the learners. Therefore, the second hypothesis predicts that students who are asked to employ more time on the computer simulation while using the simulation spend more time with the simulation and perform better on retention and transfer than do students for whom this request is absent.

Third, adding learning questions in computer simulations could overcome the problem that learners often do not learn adequately with simulations (cf. de Jong, 2006). More precisely, it is expected that answering the learning questions requires the three basic processes postulated in the SDDS model. For this reason, learning questions should encourage learners in a) searching the hypothesis space to generate a fully specified hypothesis, b) generating a prediction as well as collecting evidence and c) evaluating the collected evidence. Empirical findings (e.g. Demetriadis, Papadopoulos, Stamelos & Fischer, 2008) for ill-structured domains suggest that question prompts can foster domain knowledge acquisition and knowledge transfer, whereas the effect is moderated by different aspects of the learning setting (e.g., whether time is restricted for processing the instructional materials, see Papadopoulos, Demetriadis, Stamelos & Tsoukalas, 2009).

A quasi-experimental study (Ge & Land, 2003) measured four different student problem-solving processes (i.e., problem representation, generating solutions, making justifications and monitoring and evaluating) in an ill-structured task in the context of a lecture session. Students who received questions prompts in printed format or through the Internet outperformed those who received no prompts on all four dependent measures. While previous studies used learning questions in case-based learning in technology-enhanced learning environments, presented ill-structured tasks in the context of a lecture session, or used questions and feedback during a lecture (Campbell & Mayer, 2009), the present study attempts to extend these findings for computer simulations. Therefore, the third hypothesis predicts that students who are given learning questions (without feedback) about the content of the computer simulation while using the simulation perform better on retention and transfer than do students for whom these questions are absent.

Method

Participants

The participants were 97 undergraduate students recruited from the University of Trier (Germany). The students took part in the experiment to fulfill test subject hours. The mean age of the participants was 21.4 (*SD* = 2.8) years and the overall percentage of women was 72.2%. Most (72.2%) of the students were enrolled in psychology as their main subject. The remaining students (27.8%) were enrolled in sociology (11.3%), economics (3.1%) and other main subjects (13.4%). Participants had only superficial knowledge in the presented instructional material. Each student was randomly assigned to one of the eight treatment groups (2 x 2 x 2).

Design

The computer-presented material consisted of an illustrated introductory text and a computer simulation about the analysis of variance (ANOVA), regression analysis and the *General Linear Model* (GLM), retention and transfer tests, as well as a questionnaire about the perceived quality of the instructional material. The simulation presented two different dynamic visualisations, where the learner could change different parameters with scrollbars and radio buttons and observe the resulting effects (see Figure 1). Manipulating the different parameters resulted in a modified visualisation immediately. Learners could also change the perspective or rotate the visualisations by using scrollbars as well.

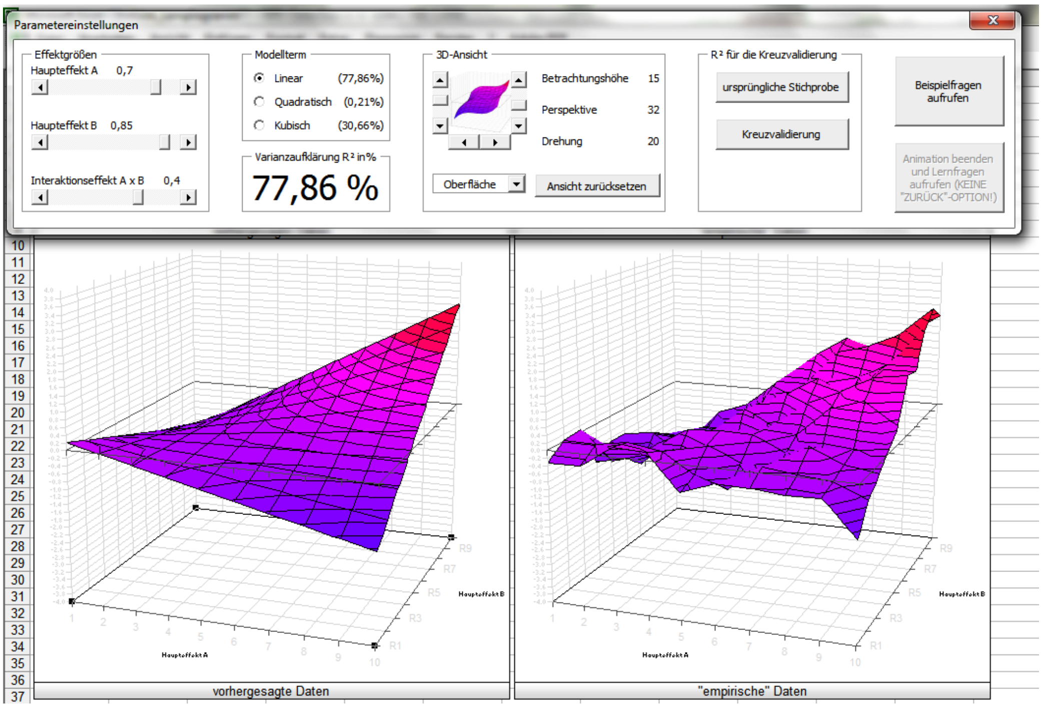

Figure 1: Selected frame from the group with learning questions. The learning question button was placed in the right upper corner ("Beispielfragen aufrufen").

The instructional advice factor (with or without instructional advice) was the first between-subject factor manipulated. The instructional advice was "Proceed systematically while experimenting with the interactive visualisation! Try to use all scrollbars and buttons separate from each other to find out what these elements exactly effectuate. Vary each scrollbar completely from left to right and also from up to down (or vice versa). Subsequently, you should modify several scrollbars and buttons concurrently to peruse systematically if and how they interact with each other!" It was presented on the text page shown immediately before the simulation. To ensure that the advice was noticed a red exclamation mark was added to the left of the advice. There were 48 participants in the group with instructional advice and 49 subjects in the group without instructional advice.

The time advice factor (with or without a request to employ more time on the computer simulation) was the second between-subject factor manipulated. The advice was "Dear participant, we would like to advise you to look at the interactive visualisation a little bit longer". It was presented during the computer simulation after the participant in the time advice condition pressed the button to finish the computer simulation. Instead of finishing, the advice appeared. If the participant pressed the button to finish the computer simulation a second time, the same time advice appeared again. Pressing the button to finish the simulation for the third time, the participant actually finished the simulation. Every participant in the time advice condition received the time advice two times, independent of time they actually spent with the simulation before the advice. There were 51 participants in the group with time advice and 46 subjects in the group without time advice.

The learning questions factor (with or without learning questions) was the third between-subject factor manipulated. Two learning questions appeared if the student pressed the button labeled "Show example questions". This button had to be pressed at least once to finish the computer simulation. The button was placed in the right upper corner (see Figure 1). After pressing the button, two example questions about the content of the computer simulation appeared in multiple choice format (six response options per question where only one answer per question was correct). Both questions were displayed in an extra window which could be closed and opened as often as required. One question was a retention question, the other a transfer question. In both cases, students received no feedback after answering the question (i.e., choosing a radio button). Neither question was used in the subsequent retention and transfer test. There were 50 participants in the group with questions and 47 subjects in the group without questions. Comparisons were made between the eight groups (2 x 2 x 2) on measures of retention and transfer.

Instrument and materials – tasks

The multimedia presentations were developed using Microsoft *Excel* and *Visual Basic Application* (VBA) and are only available in the German language. The apparatus consisted of twenty personal computer systems, each with the same 17-inch monitor (display resolution: 1280 x 1024).

For each participant, the computer materials contained the instructional material, the retention and transfer tests, a short questionnaire about the perceived quality of the instructional material, as well as a participant questionnaire soliciting information concerning the student's gender, age, field of study, number of terms, and self evaluated general computer knowledge. Time was measured separately for the introductory text, the simulation, as well as the retention and transfer tests. Click frequency for all interactive elements (scrollbar and buttons) was recorded as well.

The illustrated text in the fore field of the computer simulation consisted of nine pages containing approximately 2350 words as well as one table and five figures about the ANOVA and regression analysis. The text gave a short introduction into these statistical analyses and described how both are congruent with each other in the context of the GLM. The text also pointed to the overfitting problem in statistical analyses and explained the functionality of the subsequent presented computer simulation in detail with two additional figures.

The simulation consisted of three components. First, in the upper area of the screen ("Parametereinstellungen"), different parameters with scrollbars and radio buttons could be modified by the learner (see Figure 1). There, students could change the effect sizes ("Effektgrößen") for the two main effects and the interaction between the two predictor variables, choose between a linear, quadratic or cubic model ("Modellterm") and observe the explained variance of the model ("Varianzaufklärung"). Furthermore, students could rotate the figures and alter the perspective ("3D-Ansicht") amongst others and perform a cross-validation ("Kreuzvalidierung"). Second, manipulating the different parameters (e.g., the main effect for the predictor variable A) immediately changed the visualisation on the left side, which represented the predicted dataset ("vorhergesagte Daten") in a three-dimensional coordinate system (see Figure 1). Third, the visualisation on the right side, representing a fictitious empirical dataset (""empirische" Daten"), could be modified by testing the resulting prediction on a new dataset in order to avoid overfitting. Both visualisations were changed simultaneously by rotating the figures or by altering the perspective.

Retention is the ability to store information and retrieve or recognise the information later. This multidimensional ability is measured by testing, if learners can repeat, list, name, recognise or reproduce factual information (cf. Bloom & Krathwohl, 1956; Bloom, Madaus & Hastings, 1981; Mayer, 2005b). The retention test consisted of ten multiple choice questions. Each question included five or six response options where only one answer per question was correct. As an example, the question "Which effect was presented on the x-axis in the interactive visualisation?" contained five different response options, for instance, "Main effect A". Another question asked what model terms can be found in the visualisation. It included six different response options, for instance, a linear model term. All retention questions could be answered with the information that was given in the simulation without the inference of additional information.

Contrary to retention, transfer performance is related to the multi-faceted potential to acquire the meaning of the stored information and apply it in new contexts. The transfer test consisted of nine multiple choice questions (four to six response options where only one answer per question was correct) and one questions in open response format. For this question ("How big was the maximum explained variance that could be reached in the master sample?"), participants had to insert a number in a text box. A multiple choice transfer question asked, for instance, what does a plane (or respectively, parallel lines) in the right graph of the interactive visualisation imply for the underlying effects. In all transfer questions inferences had to be drawn from the presented information in the visualisation (cf. Bloom & Krathwohl, 1956; Bloom, et al., 1981; Mayer, 2005b). For example, the interactive visualisation in the right graph did not show a plane or parallel lines. All retention and transfer questions were created by an expert for statistical analysis and on the basis of Bloom's taxonomy of learning from (e.g. Bloom & Krathwohl, 1956; Bloom, et al., 1981).

The questionnaire (alpha = .81) about the perceived quality of the instructional material consisted of five questions, all containing 7-point Likert scales ('the more the merrier' was the perceived quality). Two questions asked how useful the dynamic visualisation was for understanding the underlying concepts and how fast the underlying concepts in the dynamic visualisation could be comprehended. In the three remaining questions, learners should judge the entire instructional material as well as the dynamic visualisation only and they had to evaluate the didactical quality of the dynamic visualisation.

Procedure

Participants were tested in groups of 1 to 20 per session. Each student was randomly assigned to one of the eight treatment groups (2 x 2 x 2) and was seated at an individual cubicle in front of a computer. The participants completed the entire experiment at their own rate and without any time limit. On average, they spent about 20-40 minutes with the instructional text and the simulation. On the introductory page, students were welcomed and thanked for participating in the experiment as well as advised to study the instructional materials carefully and to use and pay attention to the simulation precisely and extensively. While working with the simulation students no longer had access to the introductory text. After finishing the simulation participants answered the same retention and transfer questions as well as the same questionnaire about the perceived quality of the instructional material without having access to the simulation anymore. Finally, participants were thanked for their participation and debriefed.

Scoring

For the multiple choice retention and transfer questions, the participants received one point for choosing the correct response option. For the only transfer question with open response format, the subjects could gain an additional transfer point if the inserted number in the text box was within a predefined accepted narrow value range. The correct answer and score assessment for this question was defined very precisely before the study, so two independent raters agreed on 100% of this open response format transfer question. The final score was reached by adding together the student's scores on each individual retention and each individual transfer question. Therefore, a maximum score of ten points for retention and ten points for transfer could be achieved. The final score for the evaluation of the instructional material was reached by averaging each student's score on the five questions (for each question one to seven points). Hence, a minimum score of one point and a maximum score of seven points could be reached.

Results

Table 1 shows the mean scores and standard deviations for the eight different groups on measures of retention, transfer and time spent with the computer simulation (without the instructional text and the retention and transfer questions). A three-factor multivariate analysis of variance (MANOVA) was conducted, with instructional advice (with instructional advice vs. without instructional advice), time advice (with a request to employ more time on the computer simulation vs. without such a request) and learning questions (with learning questions vs. without learning questions) as between-subjects factors, and retention, transfer and time spent with the simulation as dependent measures. The assumption of homogeneity of variance was tested prior to the MANOVA and found to be tenable, Box's M (42, 12568.9) = 56.39, p = .19. Three-way analyses of variance (ANOVAs) on each dependent variable were conducted as follow up tests to the MANOVA.

Table 1: Mean score on retention and transfer tests and time spent with the computer simulation (in minutes and seconds without the instructional text and without the retention and transfer questions) and their corresponding standard deviations for the eight different groups (2 x 2 x 2)

Group				Type of measure					
				Retention		Transfer		Time	
Instructional advice	Time advice	Learning questions	Group size	Mean	SD	Mean	SD	Mean	SD
+	+	+	14	7.64	1.69	4.21	2.22	18.43	9.8
+	+	–	12	7.17	0.94	4.17	1.03	19.2	10.60
+	–	+	11	6.27	1.01	4.00	1.67	10.18	7.29
+	–	–	11	6.27	1.85	2.91	1.38	9.12	6.35
–	+	+	13	7.23	2.09	2.85	1.95	15.28	8.48
–	+	–	12	6.67	2.02	3.50	1.62	11.29	5.0
–	–	+	12	6.08	1.38	4.17	2.33	12.14	7.18
–	–	–	12	6.58	2.31	3.50	2.02	8.46	5.25

Note: "+" means "with", "–" means without. Potential scores ranged from 0 to 10 for the retention and the transfer score.

Instructional advice

Students who are advised to examine the different parameters in a simulation systematically perform better on retention and transfer than do students for whom this advice is absent.

No significant differences were found among the two groups on the dependent measures (Wilk's lambda = .98), $F(3, 87) = 0.74$, $p = .53$. The effect size (partial eta squared) was 0.03. Statistically, the null hypothesis could be accepted for an effect size of $f^2 = .15$ due to the sufficient power (1-beta > .80 for alpha = .05). Time spent with the simulation was also considered as a covariate (instead of as a dependent variable) to find out if these nonexistent learning differences (i.e. differences in retention or transfer) were at least partly contingent upon differences in the time spent with the simulation. However, the multivariate analysis of covariance (MANCOVA) showed a nonsignificant finding on the dependent measures retention and transfer as well (Wilk's lambda > .99), $F(2, 87) = 0.07$, $p = .93$. Overall, these results do not show that learners who are advised to examine the different parameters in a simulation systematically perform better on retention and transfer than do students for whom this advice is absent.

Time advice

Students who are asked to employ more time on the computer simulation while using the simulation spend more time with the simulation and perform better on retention and transfer than do students for whom this request is absent.

Significant differences were found among the two groups on the dependent measures (Wilk's lambda = .84), $F(3, 87) = 5.52$, $p < .01$. Students who were asked to employ more time on the computer simulation spent over six minutes (6 minutes and 7.1 seconds) more time with the simulation (M = 16 minutes and 15.6 seconds, SD = 9 minutes and 1.8 seconds) than did students for whom this request was absent (M = 10 minutes and 8.5 seconds, SD = 6 minutes and 38.9 seconds), $F(1, 89) = 14.23$, $MSE = 3177276.5$, $p < .001$. The effect size (Cohen's d) was .77 on time, indicating a large effect size. Students who were asked to employ more time on the computer simulation scored significantly better on the retention test ($M = 7.20$, $SD = 1.73$) than did students who did not receive instructional advice ($M = 6.30$, $SD = 1.67$), $F(1, 89) = 6.11$, $MSE = 18.41$, $p < .05$. The effect size (Cohen's d) was .25 on retention, indicating a small to medium effect size. Time spent with the simulation was also considered as a covariate (instead of as a dependent variable) in the statistical analysis.

Contrary to the foregoing analysis, an analysis of covariance (ANCOVA) showed a nonsignificant finding on the dependent measure retention, $F(1, 88) = 1.04$, $MSE = 2.71$, $p = .31$. This indicates that retention differences between the two groups (with or without a request to employ more time on the computer simulation) were at least partly contingent upon the time spent with the simulation. Students who were asked to employ more time on the computer simulation did not score significantly better on the transfer test ($M = 3.69$, $SD = 1.83$) than did students who did not receive time advice ($M = 3.65$, $SD = 1.90$), $F(1, 89) = 0.01$, $MSE = 0.04$, $p = .92$. Statistically, the null hypothesis could be accepted for an effect size of $f^2 = .15$ due to the sufficient power (1-beta > .80 for alpha = .05). The effect size (Cohen's d) was 0.02 on transfer. Time spent with the simulation was also considered as a covariate (instead of as a dependent variable). The ANCOVA showed a nonsignificant finding on the dependent measure transfer as well, $F(1, 88) = 1.27$, $MSE = 3.89$, $p = .26$. Overall, these results show that learners who are asked to employ more time on the computer simulation while using the simulation spend considerably more time with the simulation and perform better on retention, but not on transfer than do students for whom this request is absent.

Learning questions

Students who are given learning questions (without feedback) about the content of the computer simulation while using the simulation perform better on retention and transfer than do students for whom these questions are absent.

No significant differences were found among the two groups on the dependent measures (Wilk's lambda = .98), $F(3, 87) = 0.58$, $p = .63$. Statistically, the null hypothesis could be accepted for an effect size of $f^2 = .15$ due to the sufficient power (1-beta > .80 for alpha = .05). The effect size (partial eta squared) was 0.02. Time spent with the simulation was also considered as a covariate (instead of as a dependent variable). The MANCOVA showed a nonsignificant finding on the dependent measures retention and transfer as well (Wilk's lambda > .99), $F(2, 87) = 0.07$, $p = .93$. Overall, these results do not show that learners who are given learning questions (without feedback) about the content of the computer simulation while using the simulation perform better on retention and transfer than do students for whom this advice is absent.

Further findings

There was no significant interaction among two of the three between-subjects factors (instructional advice, time advice and learning questions) on the dependent measures ($.16 \le p \le .41$). The effect size (partial eta squared) was between 0.03 and 0.06. Likewise, no significant interaction was found between the three between-subjects factors on the dependent measures (Wilk's lambda > .99), $F(3, 87) = 0.09$, $p = .96$. Statistically, the null hypothesis could be accepted for an effect size of $f^2 = .15$ due to the sufficient power (1-beta > .80 for alpha = .05). Time spent with the simulation was also considered as a covariate (instead of as a dependent variable). The MANCOVA showed nonsignificant findings on the dependent measures retention and transfer as well ($.14 \leq p \leq .91$).

Furthermore, a three-factor ANOVA was conducted, with the three between-subjects factors on the dependent measure time spent with the introductory text, which was presented in the fore field of the simulation. Most of the effects (i.e., main effects and interaction effects) failed to reach significance ($.30 \leq p \leq .95$). However, the main effect for the between-subjects factor instructional advice (with instructional advice vs. without instructional advice) reaches significance, $F(1, 89) = 5.37$, $MSE = 541772.3$, $p < .05$. Students who are advised to examine the different parameters in a simulation systematically (M = 17 minutes and 30.0 seconds, SD = 5 minutes and 47 seconds) spent two minutes and 35.2 seconds more with the instructional text than did students for whom this advice was absent (M = 14 minutes and 54.8 seconds, SD = 4 minutes and 34.2 seconds). The effect size (Cohen's d) was .50 on time, indicating a medium effect size. No significant differences were found for the three between-subjects factors as well as their interactions in regard to the questionnaire about the perceived quality of the instructional material ($.14 \leq p \leq .89$). Click frequencies for all scrollbars and radio buttons in the simulation were also analysed as dependent measures with the Holm-Bonferroni method (Holm, 1979) to adjust the alpha level. No significant differences were found for the three between-subjects factors as well as their interactions.

Discussion

The goal of this research was to investigate whether instructional advice, learning questions and time advice in a computer simulation, affect learning and time spent with a computer simulation. Learners who were advised to examine the different parameters in a simulation systematically (before the simulation) performed better neither on retention nor on transfer than did learners for whom this instructional advice was absent. The advice also did not influence time spent with the simulation. Students who were asked to employ more time on the computer simulation while using the simulation spent considerably more time with the simulation and performed better on retention, but not on transfer than did students for whom this request was absent. Learning questions (without feedback) about the content of the computer simulation presented while using the simulation did not influence learning performance or time spent with the simulation. Analysing click frequencies and the questionnaire about the perceived quality of the instructional material did not reveal any significant differences for the different instructional conditions.

Overall, neither instructional advice nor learning questions influenced learning outcome, while using time advice increases learner's retention performance. For the instructional advice, the results are consistent with the findings from Rivers and Vockell (1987) who used experimentation hints like "It is wise to vary only one variable at a time" in the fore field of the simulation. This advice failed to show positive effects in regard to learning outcomes. Possibly, relatively simple instructional advice does not always improve learning outcomes in computer simulations. However, in a study from Rey (in press) the existence of even simpler advice as in the present study, increased learner's transfer performance. Overall, it can be assumed that the advice used in the present study changes handling of the simulation, but is too superficial and unspecific to improve the three basic processes postulated in the SDDS model (i.e., search hypothesis space, test hypothesis and evaluate evidence). Potentially, it would be more helpful to present simulation exercises to the learners, advise them to structure a sequence for at least some of the variables and use other scaffolding strategies. However, nonsignificant differences in click frequencies for the between-subject factor instructional advice suggest that the advice did not modify handling of the simulation at all. Potentially, the advice might not have been noticed at all.

For the time advice, the results indicate that learner's retention performance can be improved, while the transfer performance cannot. Time advice increases the time spent with the simulation and possibly, through repeating the learning content, improves pure retention score. But simple repetition seems not to imply deeper understanding respectively improving the three basic processes postulated in the SDDS model (see above). Instead, it can be assumed that most of the learners still do not know how to use the simulation adequately and therefore do not benefit from such a time advice with regard to transfer performance.

For the learning questions without feedback, the results are in accordance with the empirical findings from Papadopoulos et al. (2009). They do not show positive effects in regard to learning outcome. It can be assumed that learning questions failed to foster the three basic processes postulated in the SDDS model. Possibly, learners could benefit from learning questions, but only with corrective or explanatory feedback. In this context the feedback principle can be mentioned, which is postulated in the cognitive-affective theory of learning with media (CATLM) from Moreno (Moreno, 2005; Moreno & Mayer, 2007). According to that principle students learn better with explanatory rather than with corrective feedback. Explanatory feedback consists of providing an explanation for why learners' answers are correct or not. This explanation is based on a principle. In contrast to explanatory feedback, corrective feedback consists of only communicating whether students' answers are correct or not. Empirical evidence for the feedback principle is supported by several studies (see Moreno & Mayer, 2007; cf. also with the questioning principle postulated from Campbell and Mayer, 2009).

The nonsignificant findings for the presented learning questions can also be explained by the inadequate usage of the questions. For example, Greene and Land (2000) found that question prompting was often insufficient as a scaffold because students sometimes omitted questions or answered superficially, thereby failing to engage in deeper processing (see also Davis & Linn, 2000; Ge & Land, 2003, 2004). Possibly, learners in the present study also used the learning questions in a superficial way.

Implications and limitations

On the practical side, the recent findings emphasise that learners often have serious problems learning adequately with computer simulations. Simple instructional advice and learning questions without feedback are not always successful to alleviate this problem. Possibly, instructional advice should be highlighted in order to be noticed by learners as well as elaborated to improve the three basic processes postulated in the SDDS model, while the learning questions should contain explanatory feedback. Time advice in computer simulations should be added only if learners' pure retention should be fostered through repeating the learning content. This repetition effect seems not to affect deeper understanding, respectively improving the three basic processes postulated in the SDDS model.

The present study was limited by the short-term nature of the instructional materials (i.e., they consisted of only 20-40 minutes of concentrated instruction) and the limited genre of the instructional materials (i.e., an introductory text and a computer simulation about the analysis of variance, the regression analysis and the General Linear Model). The ability to generalise was also limited by the nature of the test (i.e., primarily multiple choice questions created by an expert for statistical analysis and given immediately after instruction) as well as the non-authentic context (i.e., as a required psychology experiment). Subsequent research is needed to determine whether the same pattern of findings would occur for other instructional materials and other contexts.

Future directions

Other types of learners should be tested as well. In the present study only undergraduate freshmen with very little or no prior knowledge about statistics were involved. Possibly, these learners could be overstrained by the presented sophisticated statistical concepts even if instructional advice and learning questions were added. It is likely that different kinds of prior knowledge could moderate the influence of instructional advice, time advice and learning questions with or without feedback in computer simulations. In this context, the expertise reversal effect postulates that design principles for multimedia learning environments (e.g., the feedback principle) depend on the prior knowledge of the learner (for more information, see Kalyuga, 2007).

Prospectively, computer simulations that are not only interactive, but at the same time adaptive, will be used more frequently in multimedia learning (cf. Van Merriënboer & Sweller, 2005). Adaptive computer simulations are simulations that react to parameter changes implemented by the user and assess the learner's behaviour. This assessment serves as a basis to modify the visualisation or to give personalised feedback to the learner. There are different kinds of user behaviour, which can be assessed. For example, the learner's way of using the different interactive elements in the simulation can be assessed (e.g., based on log files of the student's interaction, see e.g., Veermans, van Joolingen and de Jong, 2006), followed by personalised instructional or time advice to improve the learner's utilisation and to attain a deeper understanding of the presented instructional material (cf. Lin & Lehman, 1999). Overall, future studies should investigate the implications of adaptive computer simulations and adaptive learning environments for human information processing and effects for learning outcome, instead of merely focusing on their technical implementation or tailoring instructional content to relatively superficial learner attributes (Kalyuga, 2008).

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