Symposium: Supporting the use of multiple representations in multimedia learning environments

Organization:Maria Opfermann, Knowledge Media Research Center, Konrad-Adenauer-Str.40, Tübingen, Germany, m.opfermann@iwm-kmrc.de
Jan van der Meij, University of Twente, P.O. Box 217, Enschede, Netherlands, j.vandermeij@utwente.nl
Discussion: Shaaron Ainsworth, School of Psychology, University of Nottingham, University Park, NOTTINGHAM NG7 2RD, U.K, Shaaron.Ainsworth@nottingham.ac.uk

Abstract: Many learning environments contain multiple representations. Using them can lead to a deeper level of cognitive processing when learners make mental transformations between representations. However, research has revealed two problems. First, it has been shown that learners often do not make spontaneous use of such multiple options. Second, the translation process is often difficult. The papers presented in this symposium aim at supporting learners' use of multiple representations as well as their translation process. The first study provided learners with different types of representations and asked them to translate those into other representations. The second study examined the effectiveness of contextual scaffolds in computer simulations.The third study aimed at supporting hypermedia learning with multiple representations by means of metacognitive modelling and prompting of representational awareness. The fourth study investigated if sequencing dynamic representations combined with explicit instruction to relate and translate between representations has a positive effect on learning outcomes.

Study 1: Translation processes in learning with multiple representations – problem analysis in mathematics

Tina Seufert, Saarland University, Campus, 66123 Saarbrücken, t.seufert@mx.uni-saarland.de
Markus Vogel, University of Education, Reuteallee 46, 71634 Ludwigsburg, vogel02@ph-ludwigsburg.de
Roland Brünken, Saarland University, Campus, 66123 Saarbrücken, r.bruenken@mx.uni-saarland.de

In most of the domains in natural science information is conveyed by using different representational forms like graphs, tables, text or formulas. In order to construct a coherent mental representation of the domain, learners have to understand each of the single representations as well as to integrate them. The integration process can be seen as a process of mapping of corresponding elements between the different representations (Seufert, 2003). For example a text describes the growing of population and a corresponding line graph depicts this growth by an increasing line: to understand the relation between text and graph the learners have to map the concept of "growing" to the "increase" of the line. A prerequisite for this mapping process is the process of translating between textual and graphical sign systems (in other words between descriptive and depictive representations). In our example learners have to translate "growth" into "increasing line" or vice versa. As figure 1 shows, this type of transformation requires changing columns and is thus called *vertical*. Moreover, in natural science, e.g. in mathematics or chemistry, learners often have to switch between mathematical/chemical models and real-world models (Vogel, Girwidz & Engel, 2006). For example a verbal real-world task (add two apples and three apples) has to be transformed into a mathematical formula ($x = 2+3$). This type of transformation is called *horizontal* as it requires changing between the rows (see figure 1). Moreover, especially in mathematics some integration tasks require both types of transformations (e.g. mapping a verbal task and a line graph of a linear function).

Based on a large amount of empirical research we can state, that learning with multiple representations is often difficult and even leads to lower learning outcomes than learning with single representations (for an overview see Ainsworth, 1999). It is argued that these difficulties are mostly due to problems with the integration of multiple representations. The aim of our study is to find out whether these integration difficulties can be traced back to translation problems. Hence, we analyzed translation processes in the domain of mathematics. Based on the analysis of problems we want to develop instructional strategies to support translation. We hypothesized that learners task performance decreases when one type of transformation is required, and even more when both transformations are required.

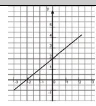
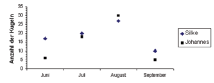
<table>
<tr><th></th><th>Description</th><th>Depiction</th></tr>
<tr><td>mathematical model</td><td>formula / equation $y = mx + n$</td><td>mathematical graph </td></tr>
<tr><td>real-world model</td><td>data table/ text
<table>
<tr><th>time in minutes</th><th>temperature in °C</th></tr>
<tr><td>0</td><td>0</td></tr>
<tr><td>1</td><td>-0,5</td></tr>
<tr><td>2</td><td>-1</td></tr>
<tr><td>3</td><td>-1,5</td></tr>
<tr><td>5</td><td>-2,5</td></tr>
<tr><td>7</td><td>-3,5</td></tr>
</table></td><td>data diagram 
</td></tr>
</table>

Figure 1. Taxonomy of representational types in mathematics.

Method

In order to test our hypotheses we developed 18 transformation tasks for all types of changes. We focused on the mathematical domain of linear functions. Learners were given for example a mathematical graph of a linear function and were asked to translate it into a linear equation or they were given a data table and were asked to produce a mathematical graph of the underlying linear function. The produced representations were rated by using a set of criteria, like correctness of scale in line graphs or correct translations, e.g. from the word "increase" to a positive value of "m" in the linear equation. In order to avoid effects of prior knowledge we provided an information sheet with the relevant aspects of linear functions before the transformation tasks had to be solved. This was important because we didn't want to assess mathematical but representational competences. In a within-subjects design with n = 30 subjects we analyzed, whether different subsets of tasks entail different performance levels: with or without vertical transformation, with or without horizontal transformation, without any, with one or with two transformations. For the vertical and horizontal transformations we also analyzed whether transformations in one direction are more difficult than in the other (description to depiction or vice versa / mathematical to real-world or vice versa).

Results

The probability of task solutions for all subsets of tasks can be seen in table 1. An ANOVA with repeated measures revealed an unexpected effect for vertical changes: performance was better when a vertical transformation was required compared to no vertical transformation ($F(1) = 38.96$, $p < .001$, $\eta 2 = .57$). The analysis of type of vertical transformation makes obvious that especially the transformation from depiction to description was difficult compared to the opposite direction ($F(1) = 8.48$, $p < .01$, $\eta 2 = .23$). With respect to the horizontal transformation we found the expected advantage for the tasks without horizontal change ($F(1) = 60.24$, $p < .001$, $\eta 2 = .68$). In this case both directions of change revealed equal results ($F(1) = 0{,}51$, n.s.). The question whether task difficulty increased with the number of required changes cannot be answered clearly: the three subsets of tasks differ significantly ($F(2) = 18.39$, $p < .001$, $\eta 2 = .39$). However, we found the expected lower scores for one change compared to no change (a priori contrast: $F(1) = 115.07$, $p < .001$, $\eta 2 = .80$). but again better scores when two changes were required (a priori contrast with one change: $F(1) = 10.38$, $p < .01$, $\eta 2 = .26$). To enlighten the unexpected result patterns we analyzed the tasks more deeply and found out that the type of representation which was presented (and only had to be read) had no significant influence on performance, but that performance differed considerably for the types of representations which had to be produced: Especially the production of equations and texts were very difficult, whereas tables were the easiest, followed by data diagrams and linear graphs.

Table 1: Probability of task solution and standard deviation for different subsets of tasks.

without vertical change	.53	.22	maths to real-world	.53	.25
with vertical change	.67	.18	real-world to maths	.56	.21
description to depiction	.72	.18	without any change	.77	.22
depiction to description	.61	.23	with one change	.57	.19
without horizontal change	.69	.19	with two changes	.69	.22
with horizontal change	.53	.19			

Discussion

To summarize the results, we found that students had enormous problems in transforming different types of representations. For half of the tasks the probability of task solution was less than 60%. However, despite our theoretical assumptions the difficulties were not that closely related to the type of transformation. For the vertical change dimension we found even reverse results: i.e. that it is not relevant whether learners have to change between descriptions and depictions. Instead the difficulties go back to specific production affordances, i.e. to verbalize the meaning of an equation/graph etc. or to extract an equation from a diagram/text/table etc. The horizontal change dimension on the other hand revealed the expected results, which support other findings from maths studies (see Vogel et al., 2006). As a next step we want to develop instructional aids for translation with a special focus on the verbalization of the meaning of different mathematical representations.

References

Ainsworth, S. (1999). The functions of multiple representations. *Computers and Education, 33*, 131-152.

Seufert, T. (2003). Supporting coherence formation in learning from multiple representations. *Learning and Instruction, 13*, 227-237.

Vogel, M., Girwidz, R. & Engel, J. (2006). Supplantation of Mental Operations on Graphs. *Computers & Education*, in press, doi:10.1016/j.compedu.2006.02.009.

Study 2: Using Narratives as Contextual Scaffolds for Science Simulations

Jan L. Plass[1], Bruce Homer[2], Yan Wang[1], Minchi Kim[3], Catherine Milne[1], Trace Jordan[1]
1. Program in Educational Communication & Technology, New York University; Email: jan.plass@nyu.edu
2. PhD Program in Educational Psychology, the Graduate Center, CUNY
3. Educational Technology, Department of Curriculum and Instruction, Purdue University

Research has made a compelling case that the effectiveness of active learning approaches such as discovery learning, problem-based learning, and experiential learning depends on the level of guidance learners receive. Approaches where learners receive only minimal instructional guidance have recently come under considerable criticism by science educators and educational psychologists (Kirschner, Sweller, & Clark, 2006). Many ways of providing instructional guidance have been explored. In technology-based learning environments, one of the most common approaches to provide instructional guidance is the use of scaffolds. Scaffolds serve to support learners in specific areas to facilitate the learning process (Wood, Bruner & Ross, 1976).

The present study investigated the use of contextual scaffolds for computer simulations for science education. In particular, we were interested in the differential effects of using case examples versus narrative structures to facilitate learners' knowledge generation in chemistry computer simulations. Research suggests that narrative structures are effective tools for make meaning and understanding experiences, including learning experiences (Bruner, 1991; CTGV, 1992). Even for scientific knowledge, which is typically presented through arguments in which embedded empirical evidence supports specific models and theories, there appears to be a cognitive bias towards linear narrative in the construction of knowledge (Abbott, 2003).

In science education, the use of narratives has been extensively studied in inquiry-oriented classroom settings. There are three major functions of narratives that set them apart from case examples. Narratives serve as: (1) conceptual links between students' experiential knowledge based on their daily experiences and paradigmatic structural knowledge (based on the use of evidence for supporting scientific argument) often found in abstract form in science textbooks (Bruner, 1986; Kurth, Kidd, Gardner, & Smith, 2002), (2) semantic cues that capture students' attention at the beginning of inquiry and further assist knowledge comprehension (Graesser, 1981), and (3) a method of connecting complex ideas and events by providing structures and sequences of phenomena under investigation (Norris et al., 2005). Over time, narrative provides a coherent ideational structure that permits the linking and integration of content components (Talmy, 2000). This process of embedding simulations in a narrative structure that connects phenomena and abstract explanatory models may help resolve a significant problem in science learning: Symbol systems often remain referentially isolated in science classrooms, and students are not provided with opportunities to integrate the different symbol systems that can be used alternatively to describe the same phenomenon (Roth et al., 1997).

The present study investigated the effectiveness of narratives as contextual scaffolds for science simulations. The simulations were developed as part of the *Molecules and Minds* project, a 3-year study funded by the US Department of Education's Institute of Education Sciences to develop computer simulations for high school chemistry. The current study compared three methods of providing a context for the simulation: narratives, case examples and a baseline control. It was hypothesized that narratives would result in improved learning compared to the case examples and the baseline control.

Method

Participants were students from a large rural high school in Texas (60% females). Of the initial 227 participants, missing data excluded 21. For the remaining 206 students, 77% identified as Hispanic, 15% as white and 8% as black, Asian or other ethnic background. The students were from 10th grade (63%) and 11th grade (37%).

At the beginning of the experiment, students were asked to complete a survey measuring their interest in chemistry. Students were then given a knowledge pretest consisting of eight multiple-choice questions on the topic of Gas Laws. Before they started exploring a simulation of the *Ideal Gas Law*, students were randomly assigned to three groups with different content scaffolding. One group was given a case example illustrating the manifestation of Gas Laws in real life situations. Another group was presented with a narrative in which observations made in the story could be explained by using the gas laws. The third group was the baseline group that was not given any content scaffolding. After exploring the simulation, students were given a knowledge posttest consisting of 15 multiple-choice questions. Students were also given a transfer test with five real-life problems. Finally, all students received a brief survey about the cognitive load they experienced during their exploration of the simulation.

Analysis and Results

Outlier analysis identified four participants who spent less than 30 seconds and made 3 or less clicks on the simulation. They were excluded from the analysis. In order to testing if different content scaffolding had an impact on students' click count and time on task during the exploration of the simulation, regression analyses were conducted separately. After controlling for students' interest in chemistry, regression analysis results showed that narrative scaffolding condition was a significant predictor of students' time on task ($F_{2, 198} = 6.185$, $p = .002$) and click counts ($F_{2, 198} = 4.168$, $p = .017$). This indicated that scaffolding was effective in increasing participants' engagement in the learning.

The study results also showed that cognitive load was significantly predicted by students' pretest scores ($F_{1, 199} = 34.712$, $p < .043$) and their interest in chemistry ($F_{1, 199} = 5.889$, $p = .016$). The higher students' pretest scores, the lower the cognitive load they experienced during their interaction with the simulation. Also, the more interest students had in chemistry, the lower the cognitive load they experienced.

Students' pretest scores and scaffolding differences were used to predicting their posttest scores. Regression analysis results indicated that pretest score ($F_{1, 219} = 142.909$, $p < .001$) and scaffolding difference ($F_{1, 219} = 3.194$, $p = .043$) were significant in predicting posttest score. That is, students with higher pretest scores and who had scaffolds performed significantly better than other students. The group having a narrative story as content scaffolding had the highest posttest group mean. After controlling for pretest scores, students in the narrative scaffolding group performed significantly better than the example scaffolding group ($F_{1, 219} = 2.847$, $p = .046$). Time on task had no significant effect on the posttest scores.

The students' performance on the transfer test was also explored. In the transfer questions, students were either asked to explain or make suggestions relating the gas laws to a real life phenomenon (e.g. why tire is flat, how to prevent aerosol from exploding). The narrative scaffolding group again had highest group mean on transfer test scores, followed by the example scaffolding group and then the baseline group. However, the difference among the three groups was not significant.

Discussion and Conclusions

Our results indicated that narrative scaffolds were better able to facilitate learning from computer-based science simulations than case examples or no scaffolds. These results support anecdotal evidence we obtained in prior research indicating that participants use the narrative during the process of exploring the simulations to describe the phenomena under investigation and to connect what they have experienced to abstract explanatory models. This research provides initial evidence for the effectiveness of narratives as contextual scaffold in computer-based science simulations. Future research is required to verify our findings and expand them to different contents and settings.

References

Brown, A. (1992). Design experiments: Theoretical and methodological challenges in creating complex interventions in classroom settings. *The Journal of Learning Sciences*, *2*(2), 141-178.

Bruner, J. (1999). Postscript: Some reflections on education research. In E. C. Lagemann & L. S. Shulman (Eds.), *Issues in education research: Problems and possibilities* (pp. 399-409). San Francisco: Jossey-Bass.

Hawkins, J., & Pea, R. D. (1987). Tools for bridging the cultures of everyday and scientific thinking. *Journal for Research in Science Teaching*, *24*, 291-307.

Lave, J. (1987). *Cognition in practice*. New York: Cambridge University Press.

Wood, D., Bruner, J., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of child psychology and psychiatry, 17*, 89-100.

Study 3: The benefits of instructional support in hypermedia learning

Maria Opfermann, Peter Gerjets, Knowledge Media Research Center,
Konrad-Adenauer-Str. 40, 72072 Tuebingen, Germany,
Email: m.opfermann@iwm-kmrc.de, p.gerjets@iwm-kmrc.de
Katharina Scheiter, Eberhard Karls University, Konrad-Adenauer-Str. 40,

72072 Tuebingen, Germany, k.scheiter@iwm-kmrc.de

When trying to bridge the gap between multimedia and hypermedia, one can share the view of Rouet and Levonen (1996) or Jonassen (1996) and see hypermedia as an integration of multimedia with hypertext elements. That is, learners have access to information that can include multiple representational codes and address different sensory modalities. Additionally, this information can be retrieved in multiple ways, linearly as well as nonlinearly. Prior research in hypermedia learning has shown that learners are not always able to benefit from the multiple options that such environments offer, that is, they are overloaded by and/or do not use their freedom with regard to navigational and representational choices. In other words, they are not able to self-regulate their learning with the environment. Authors like Azevedo (2005) or Bannert (2005) assume that it might well be that learners do not lack those abilities completely but that they may need to be prompted or trained to display sophisticated learning strategies. Our study thus investigated whether hypermedia learning can be enhanced by means of two forms of instructional support. More specifically, we were interested in the relationship between instructional support, individual learner characteristics, and learning outcomes.

Method and procedure

The learning environment we used to investigate our research questions was a hypermedia environment that aimed at conveying basic principles of probability theory by means of worked examples which show the problem statement, solution steps, and final solution for problems from different probability categories (e.g., the probability to correctly guess the three medal winners out of a race of seven). For each example, learners could choose whether they wanted to retrieve it with arithmetical information only, enrich it with written or spoken text or animations or use any combination of these. We used a 2*2 design varying the following factors: metacognitive tool / no metacognitive tool, prompting of representational choices / no prompting of representational choices. The metacognitive tool that was used in two of the resulting four conditions was a video displayed at the *beginning of the learning phase* that aimed at supporting the metacognitive monitoring and evaluation of learners. When prompting of representational choices took place, learners received explanations of the advantages and disadvantages of the respective representational formats *directly before they chose a format* for the respective worked-out example they were about to have a look at. These variations result in the following four experimental conditions: (1) No metacognitive support / no representational prompts, (2) Metacognitive support / no representational prompts, (3) No metacognitive support / representational prompts, and (4) Metacognitive support / representational prompts.

Participants

Participants were 145 students from German schools with an average age of 16 years. There were 61 female and 81 male students. They were assigned to one of the four experimental conditions randomly. The studies were conducted as group settings in the schools' computer rooms, that is, the classes took part as a whole, but each participant worked on a computer on his / her own.

Procedure

Before working with the learning environment, students filled out a comprehensive questionnaire that aimed at assessing learner characteristics, including metacognitive strategies. Directly after learning, metacognitive activities were assessed by means of an online questionnaire. The learning environment consisted of a personal data questionnaire, a short technical instruction, a pre-test with 12 items to assess prior knowledge concerning probability theory, an introduction to the domain, the example-based learning phase that was subject to experimental manipulation, and a post-test with 19 items, whereby eight items were similar to those in the pre-test and therefore suitable to measure knowledge gains. Learners could work through the environment on their own pace, look at examples repeatedly, or proceed to the posttest whenever they thought they had learned enough.

Results

Descriptive data show that of the 12 pre-test items, learners answered between 2 and 9 correctly with an average of 5.59 ($SD = 1.68$). The four experimental conditions did not differ with regard to pretest scores.

The further data analysis revealed some surprising results. Learners in all conditions achieved significant knowledge gains, that is, they improved from pre- to post-test ($t(144) = 7.60$; $p < .001$). However, contrary to our expectations, the best results and highest knowledge gains were achieved by learners who received neither representational prompting nor metacognitive modelling, followed by learners who received prompting but no modelling or modelling but no prompting. The lowest knowledge gains were achieved by learners who received metacognitive modelling and representational prompting (see Figure 1). As revealed by an ANOVA, the overall group difference was significant ($F(3,141) = 3.837$; $p = .011$). This effect can mainly be traced back to the difference between modelling and no modelling ($F(1,141) = 8.753$; $p = .004$), while the difference between prompting and no prompting does not reach statistical significance ($F(1,141) = 2.709$, $p = .102$). There was, however, an interaction between metacognitive activities and experimental condition. In short, providing modelling or prompting did not seem to make a difference for learners scoring low on the metacognitive scales. For sophisticated learners, however, providing additional instructional support appeared to be highly detrimental ($F(1,67) = 7.22$; $p < .01$).

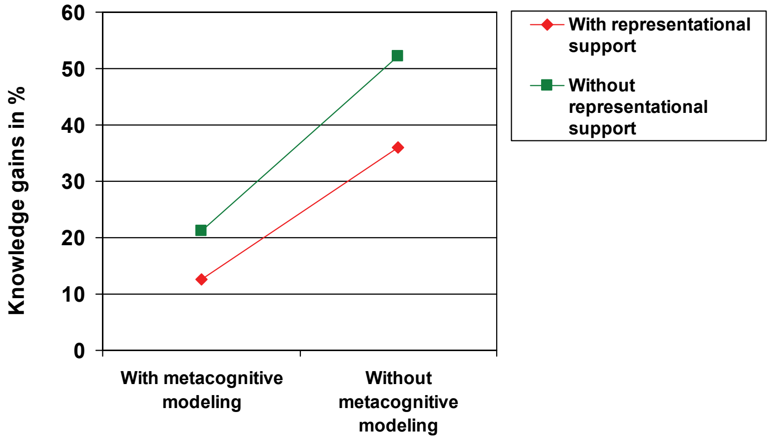


Figure 1. Knowledge gains for the four experimental conditions.

An interesting finding is that learners chose the representational formats that contained animations to a significantly higher extent than formats that did not contain animations. However, this choice did not relate to performance. Additionally, written text + animation were chosen significantly more often by participants receiving modelling than by those not receiving modeling.

Discussion

The findings of the study were partly surprising. Although all learners achieved significant knowledge gains after learning, they did not benefit from additional instructional support. This refers to their overall performance as well as to their learning behaviour. With regard to representational choices, it was found that independently of representational prompting, multiple representations that contained animations were preferred. This might be due to motivational or novelty effects. With regard to performance, it was found that learners who already possess sophisticated metacognitive abilities/knowledge do not need additional instructional support. It might even hinder their learning when metacognitive modelling as shown in the video demonstrates strategies or thinking other than what a sophisticated learner has used so far, therefore interfering with his learning behaviour. For learners with no metacognitive strategies or less sophisticated metacognitive abilities, such instructional support on the other hand might provide them with ideas of how to structure and regulate their learning. However, the question still remains whether all learners are generally better off with no instructional support at all or whether the video and the prompting devices were just not designed in an optimal way. To further investigate these questions, we are currently working on a study on fading of multiple representations as another way of fostering the benefits from using representations in hypermedia learning. Results of both studies will be presented and discussed at the symposium.

References

Azevedo, R. (2005). Using hypermedia as a metacognitive tool for enhancing student learning? The role of self-regulated learning. *Educational Psychologist, 40,* 199-209.

Bannert, M. (2005). Explorationsstudie zum spontanen metakognitiven Strategie-Einsatz in hypermedialen Lernumgebungen. In C. Artelt & B. Moschner (Eds.). *Lernstrategien und Metakognition: Implikationen für Forschung und Praxis* (pp. 127-151). Münster: Waxmann.

Jonassen, D. H. (1996). *Computers in the classroom. Mindtools for critical thinking.* New Jersey: Prentice Hall.

Rouet, J. F., & Levonen, J. J. (1996). Studying and learning with hypertext: Empirical studies and their implications. In J.-F. Rouet, J. J. Levonen, A. Dillon, & R. J. Spiro (Eds.), *Hypertext and Cognition* (pp. 9-23). Mahwah, NJ: Erlbaum.

Study 4: Sequencing Multiple Dynamic Representations - Supporting students' learning with multiple representations in a dynamic simulation-based learning environment

Jan van der Meij, Ton de Jong, University of Twente, Faculty of Behavioural Sciences,
Department of Instructional Technology,
Email: j.vandermeij@utwente.nl, a.j.m.dejong@utwente.nl

The ability to relate multiple representations and translate between them assists students in deeper domain knowledge acquisition. Connecting different representations forces learners to reflect beyond the boundaries and details of the first representation to anticipate on correspondences in the second (Petre, Blackwell, & Green, 1998). To relate representations, learners have to mentally search for similarities and differences. To translate between representations, learners need to interpret the effects that changes in one representation have on corresponding representations. An important requirement for learning with multiple representations in simulation-based learning environments is how to support learners in the processes of relating and translating. Both integration and dynamic linking of representations (Ainsworth & Peevers, 2003; Chandler & Sweller, 1991; van der Meij & de Jong, 2006) are of proven value. Physical integrated representations appear to be one representation. With dynamically linked representations, actions performed on one representation are automatically shown in all other representations. Another way to support learners in simulation-based learning environments, is providing model progression (White & Frederiksen, 1990). Based on the model progression used, the number of representations can be increased iteratively. As a result, the number of relations and possible translations are increased likewise. Starting with a few relations and possible translations and then introduce more relations and possible translations step-by-step might support learners in relating the representations and translating between them. This paper reports the results of two studies in which different types of support for relating and translating between representations were examined.

Study 1

In study one, two versions of the same simulation-based learning environment covering the physics topic of moments were compared: a learning environment providing the representations step-by-step (R-Step condition) and a learning environment providing all representations at once (R-Once condition). Subjects were 88 students at the start of their first year of secondary vocational education. The simulation interface contained five representations: (1) a concrete representation (animation of an open-end spanner), (2) a diagrammatic representation (an abstract representation of the variables playing a role in the concrete situation), (3) a numerical representation (showing the values of the variables involved), (4) a dynamically changing equation and (5) a dynamically changing table (showing one row that was dynamically updated when variables were manipulated by the subjects). Prior knowledge was measured with a pre-test containing domain items and transfer items. Learning results were measured with a post-test containing domain items, transfer items, relate items and translate items. The domain items tested whether the subjects were able to reproduce the content they were explicitly asked to explore in the learning environment. The transfer items tested the ability of the subjects to apply their acquired knowledge in new situations. The relate items asked students to relate similar variables from representations with different representational codes. To be able to answer translate items correctly, the subjects had to make a mental translation from manipulations on one representation to the effects in another representation. Overall, we found that the subjects learned from working in the learning environment; the post-test scores on the domain items and transfer items were significantly better than the pre-test scores. Despite our expectations, no differences were found between the two experimental conditions. The subjects learned equally well regardless of the way in which the representations were presented. Also, the extent to which the subjects experienced complexity of both the topic and the learning environment did not differ between the experimental conditions.

Study 2

While study one focused on surface level support, in study two we examined the effect of providing hints and prompts to encourage the subjects to translate between representations. Two versions of the same simulation-based inquiry learning environment on the physics topic of moments were compared. One learning environment provided all representations at once and instructional support focused solely on relations between the domain variables (R-Once condition). The second learning environment provided the subjects with representations step-by-step and with instructional support that focused additionally on relating representations and translating between them (R-Step condition). Subjects were 86 students from secondary vocational education (first year) and 125 students from pre-university education (third year). The simulation interface contained seven representations: (1) a concrete representation (animation of a tackle, an open-end spanner or car crane), (2) a diagrammatic representation, (3) a numerical representation, (4) a dynamically changing equation, (5) a moment-arm graph, (6) a moment-force graph and (7) a dynamically changing table. Prior knowledge was measured with a pre-test containing domain items and transfer items. Learning results were measured with a post-test containing domain items, transfer items, relate items and translate items. To control for the influence of differences in cognitive load, we used an electronic questionnaire to ask subjects to rate their cognitive load four times as they worked with the learning environment. Overall, we found that subjects learned from working with the learning environment. Post-test scores were significantly better than pre-test scores. As expected, we found that sequencing representations combined with instructional support focusing on relating and translating representations did lead to better learning outcomes. However, this was only found for the domain test items. A trend, in favour of the R-Step condition, was found on relate items. No differences were found on transfer items and translate items. Subjects in the R-Step condition reported higher cognitive load scores. Subjects did not, however, discriminate between cognitive load types. As a consequence, we were not able to identify what type of load caused the higher cognitive load of the R-Step condition.

In the symposium the results of both studies will be discussed. The discussion will focus on how to support relating and translating between representations and it's consequences for the design of simulation-based learning environments.

References

Ainsworth, S. E., & Peevers, G. J. (2003). *The Interaction between informational and computational properties of external representations on problem-solving and learning.* Paper presented at the 25th Annual Conference of the Cognitive Science Society, Boston, Massachusetts, USA.

Chandler, P., & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction, 8*, 293-332.

Petre, M., Blackwell, A. F., & Green, T. R. G. (1998). Cognitive questions in software visualization. In J. Stasko, J. Domingue, M. Brown & B. Price (Eds.), *Software visualization: Programming as a multi-media experience* (pp. 453-480). Cambridge, Massachusetts: MIT Press.

van der Meij, J., & de Jong, T. (2006). Learning with multiple representations: Supporting students' learning with multiple representations in a dynamic simulation-based learning environment. *Learning and Instruction, 16*, 199-212.

White, B. Y., & Frederiksen, J. R. (1990). Causal model progressions as a foundation for intelligent learning environments. *Artificial Intelligence, 42*, 99 -57.