

DANIEL BODEMER

CAN ACTIVE INTEGRATION OF MULTIPLE REPRESENTATIONS FOSTER SIMULATION-BASED LEARNING?

Abstract. Discovery learning with computer simulations is a demanding task for many learners. Frequently, even fostering systematic and goal-oriented learning behavior does not lead to better learning outcomes. This can be due to missing prerequisites such as the coherent mental integration of different types of representations comprised in the simulations and in the surrounding learning environment. Our own prior studies demonstrated that learning performances can be enhanced by encouraging learners to interactively and externally relate different static sources of information to each other before exploring dynamic and interactive visualizations. In an experimental study addressing the domain of mechanics it was largely confirmed that the active integration of representations can improve simulation-based learning outcomes.

1. INTRODUCTION

Computer-based learning environments increasingly comprise simulations in terms of dynamic and interactive visualizations to illustrate complex processes and abstract concepts. These simulations may be highly interactive in that they allow learners to change input variables by entering data or by manipulating visual objects and to observe the consequences of these changes in the dynamic visualizations as well as in additional representations such as numeric displays, formulas or text labels.

The conceptual model underlying the simulations has frequently to be inferred by the learners in processes of discovery learning, which correspond to the steps of scientific reasoning: defining a problem, stating a hypothesis about the problem, designing an experiment to test the hypothesis, carrying out the experiment and collecting data, evaluating the data, and (re-)formulate a hypothesis. The use of simulations frequently aims at inducing active learner behavior and constructive learning processes (e.g., de Jong & van Joolingen, 1998; Rieber, Tzeng & Tribble, in press). Learners have to self-regulate their learning behavior in order to discover the underlying conceptual model, which is assumed to lead to the acquisition of deeper domain knowledge (e.g., Schnotz, Boeckeler, & Grzondziel, 1999). However, it has shown that learners encounter difficulties in all phases of the discovery learning process. For example, learners have problems formulating useful hypotheses, designing appropriate experiments, and evaluating the output variables adequately (e.g., de Jong & van Joolingen, 1998; Njoo & de Jong, 1993; Reigeluth & Schwartz, 1989; Reimann, 1991). Moreover, many learners have difficulties in planning their experiments in a systematic and goal-oriented way and therefore interact with the simulations rather randomly (e.g., de Jong & van Joolingen, 1998; Schauble, Glaser, Raghavan, & Reiner, 1991).

Additional problems may be caused by the dynamic visualization of the simulated concepts. On the one hand the externalization of dynamic processes may

prevent learners from performing cognitive processes relevant to learning on their own (e.g., Schnotz et al., 1999). On the other hand dynamic visualizations may overburden the learners' cognitive capabilities due to large amounts of continuously changing information, particularly if the output variables are represented as non-interactive animations that do not provide learners with the possibility to adjust the playback speed or to watch single frames (e.g., Lowe, 1999). In order to cope with these requirements, learners frequently make use of a strategy that limits their processing to selected aspects of a dynamic visualization, which are often not the most relevant aspects of the visualization, but rather those that are most perceptually compelling (cf. Lowe, 2003).

In order to support simulation-based discovery learning it has been suggested to structure the learners' interactions with the learning environment (e.g., van Joolingen & de Jong, 1991). Typically, these support methods guide learners to focus on specific variables of the underlying model, to generate hypotheses about relationships between these variables, to conduct experiments in order to test the hypotheses, and to evaluate the hypotheses in light of the observed results. Furthermore, various instructional support methods have been developed to facilitate specific processes of discovery learning, such as offering predefined hypotheses or providing experimentation hints (e.g., Leutner, 1993; Njoo & de Jong, 1993; Swaak, van Joolingen & de Jong, 1998). However, empirical results regarding these methods of instructional guidance are ambiguous (cf. de Jong & van Joolingen, 1998). Learners frequently did not make sufficient use of the instructional support to increase their learning outcomes.

One way to explain these findings is that learners lack prior knowledge necessary to benefit from complex visualizations. Learners who do not know enough about the domain of the visualized and simulated concept have problems processing complex dynamic visualizations and to interact with them in a goal-oriented way, even if they have enough information about useful learning behavior (cf. Leutner, 1993; Lowe, 1999; Schauble et al., 1991). Another reason – which is not independent from prior knowledge – is the difficulty of interconnecting multiple representations. Usually, simulations are embedded in multimedia learning environments and presented in combination with symbolic external representations such as text and formulas. These different kinds of representations may complement each other, resulting in a more complete representation of the illustrated concept (e.g., Ainsworth, 1999; Larkin & Simon, 1987). Both Mayer (1997, 2001) in his theory of multimedia learning and Schnotz and Bannert (1999, 2003) in their integrative model of text and picture comprehension place emphasis on the importance of integrating textual and pictorial information into coherent mental representations during multimedia learning. However, learners are frequently not able to systematically relate multiple external representations to each other. As a consequence, these learners fail to integrate the different external representations into coherent mental representations, resulting in fragmentary and disjointed knowledge structures (e.g., Ainsworth, Bibby, & Wood, 2002; Seufert, 2003). Accordingly, to facilitate simulation-based learning it seems to be important not only to support learners in dealing with the dynamics and the interactivity of the

ACTIVE INTEGRATION OF MULTIPLE REPRESENTATIONS

simulations, but also to help them in relating the dynamically visualized information to corresponding information of other external representations.

To facilitate learning with multiple external representations it has been repeatedly suggested to present textual and pictorial information in a spatially integrated format instead of presenting them separately from each other in a “split-source” format (e.g., Chandler & Sweller, 1991, 1992; Mayer, 1997, 2001; Tarmizi & Sweller, 1988). According to cognitive load theory (Sweller, 1988; Sweller, van Merriënboer, & Paas, 1998) this can reduce unnecessary visual search resulting in a decrease of cognitive load and thus better learning. Another suggested method to support learners in making connections between different sources of information is to link the features of multiple representations by various symbolic conventions such as using the same color for corresponding entities in different representations (e.g., Kalyuga, Chandler, & Sweller, 1999; Kozma, 2003; Kozma, Russell, Jones, Marx, & Davis, 1996). While these instructional suggestions have the potential to reduce cognitive load, they do not directly support learners in constructing meaningful knowledge. Learners may nevertheless remain rather passive, concentrating on surface features of the visualizations and they may still be unable to mentally process and integrate the represented information in an adequate way (cf. Ploetzner, Bodemer & Feuerlein, 2001; Seufert, 2003).

Bodemer, Ploetzner, Feuerlein & Spada (in press) tried to initiate more active processes of coherence formation by encouraging learners to systematically and interactively integrate different multiple representations in the external environment. Learners were provided with spatially separated pictorial and symbolic representations on the screen and were asked to relate components of familiar representations to components of unfamiliar representations by dragging the symbolic represented elements and dropping them within the visualizations (see Figure 1).

This external process corresponds largely to the mental process of structure mapping as described by Gentner (1983; Gentner & Markman, 1997) and Schnotz and Bannert (1999). While (inter-)actively relating different sources of information is intended to directly support coherence formation, the simultaneous construction of an integrated format is supposed to gradually reduce unnecessary cognitive load (e.g., Chandler & Sweller, 1991, 1992). Bodemer et al. (in press) were able to demonstrate that – compared to the presentation of information in a pre-integrated or in a split-source format – learning outcomes can be improved significantly when learners actively integrate static information before interacting with dynamic visualizations.

Bodemer et al. (in press) found the largest benefit of active integration when teaching extremely complex statistics concepts. In this paper an experimental study will be described which investigates possible benefits of active integration in another application domain with a slightly lower degree of complexity. It is hypothesized that also in less complex domains learners who actively integrate multiple representations will outperform those learning with a pre-integrated format. However, the advantage of active integration should rise with the degree of complexity of the learning material.

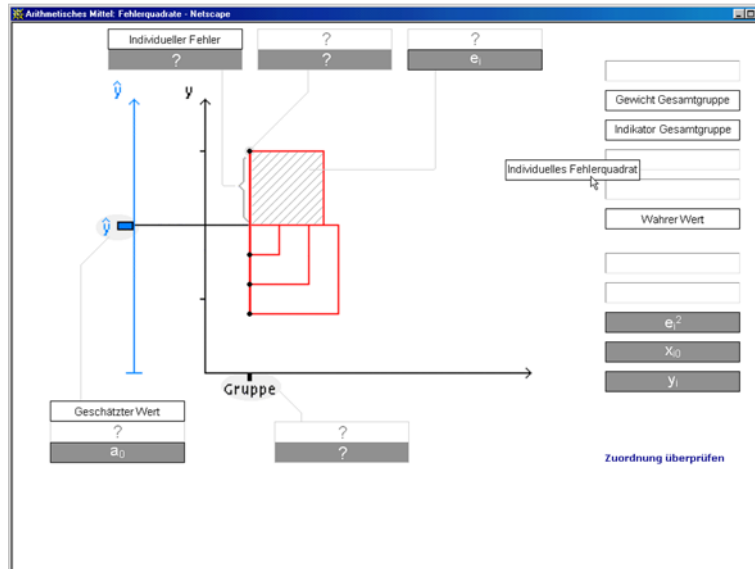


Figure 1. Active integration of information while learning statistics
(cf. Bodemer et al., in press).

In order to avoid influences of assessment on the processes of discovery learning, Bodemer and his colleagues assessed the learning outcomes only after the learners had interacted with the dynamic visualizations. Thus they could not identify if knowledge has been acquired already during the process of active integration or afterwards during the process of discovery learning or both. In the study described below the learners' knowledge has been assessed both after integrating static representations and after interacting with dynamic visualizations. It is hypothesized that already the active integration of static representations can lead to better learning outcomes. Additionally, learners who integrate multiple representations actively should improve comparatively more during simulation-based discovery learning.

2. METHOD

In this experimental study the participants learned various mechanics concepts in two consecutive learning phases. In the first learning phase they were provided with symbolic representations and static versions of dynamic and interactive visualizations. In the second learning phase they explored dynamic and interactive visualizations in a self-guided way.

ACTIVE INTEGRATION OF MULTIPLE REPRESENTATIONS

2.1. Design

The experiment used a 2 x 2 factorial design with repeated measures on the second factor. The first factor addressed two levels of *information integration*, which was varied in learning phase 1: (1) presentation of the information in a pre-integrated format and (2) active integration of information. In the first condition the learners had to deal with visualizations that were already labeled while in the second condition the learners had to establish a relationship between the symbolic representation and the visualizations by dragging and dropping the symbolic representations onto the visualizations. The within-subjects factor was time of assessment: After the integration of multiple representations (test 1) and after the exploration of dynamic and interactive visualizations (test 2).

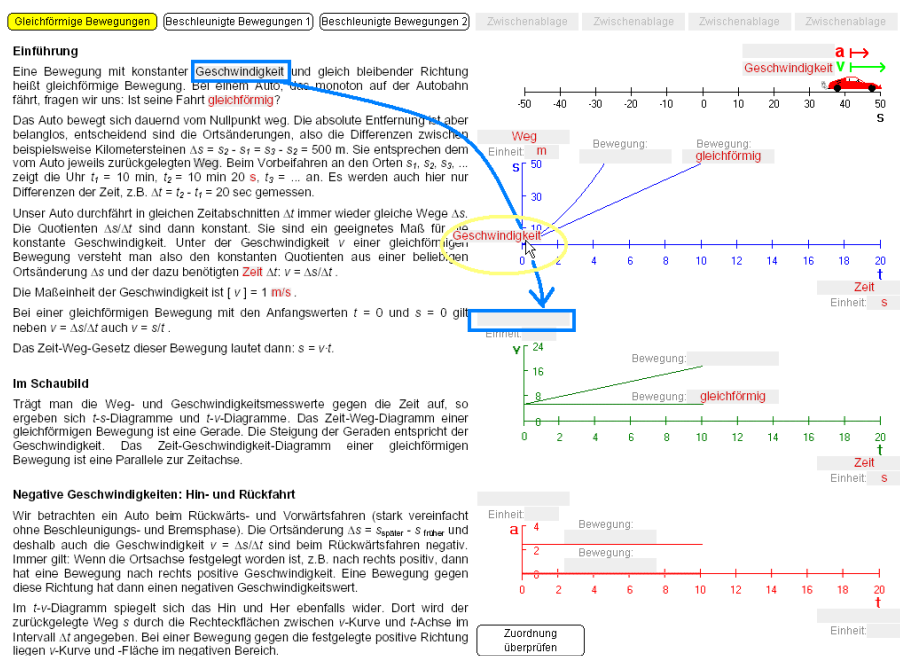


Figure 2: Active integration of information about mechanics concepts (learning phase 1).

2.2. Participants

Forty-eight students (22 males and 26 females, aged 19 to 31) of the University of Tuebingen were randomly assigned to each of the two experimental conditions. They were paid for their participation. To prevent a high level of prior knowledge students of Mathematics and Physics were excluded as participants.

2.3. Material

The *application domain* was comprised of various mechanics concepts, such as uniform and accelerated motion in one dimension. The *instructional material* consisted of two parts corresponding to the two learning phases:

(1) an instructional text accompanied by static visualizations, presented in the first learning phase on a computer (cf. Figure 2). The instructional text covered the left side of the screen and comprised three pages between which the learners could switch back and forth. The right half of the screen showed static versions of dynamic and interactive visualizations comprising the sketch of a moving car with corresponding velocity and acceleration vectors, a position-time graph, a velocity-time graph, and an acceleration-time graph. The presentation differed according to the two experimental groups of the first factor. In the group with *pre-integrated information* components of the visualizations were labeled with textual and algebraic information; whereas in the *active integration* group the learners interactively related the textual and algebraic information from the instructional text to the visualizations and thus created an integrated format on their own.

(2) dynamic and interactive visualizations, which were presented in the second learning phase (cf. Fig. 4). The visualizations were taken from the interactive learning environment PAKMA (Blaschke & Heuer, 2000). They correspond to the graphs of learning phase 1 with the addition that they could be modified by interactively changing variables and by running animated motion sequences.

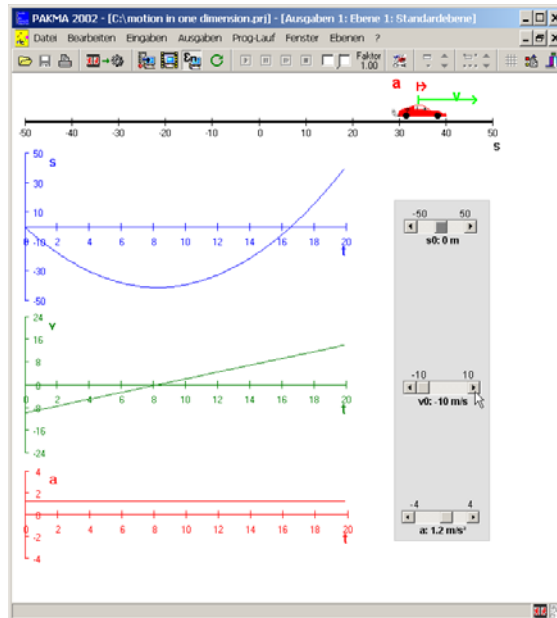


Figure 3: Dynamic simulation displaying motion in one dimension (learning phase 2).

ACTIVE INTEGRATION OF MULTIPLE REPRESENTATIONS

The *test material* consisted of a knowledge test, given to the learners prior to the first learning phase, and two tests, which assessed the knowledge after each of the two learning phases. The tests were made up of different types of questions, which all required reasoning and transfer, and contained graphical elements in either the question or the answer or both: (1) questions which addressed transformations from textual to graphical representations, (2) questions which addressed transformations from graphical to textual representations, and (3) questions which addressed transformations within graphical representations. The pre-test and the first post-test consisted of six questions (two of each type); the second post-test consisted of 12 questions (four of each type). The participants' answers were scored by two independent raters.

2.4. Procedure

At the beginning of the experiment, all participants took the pre-test (20 minutes). Thereafter, learners of the condition active integration of information could train dragging and dropping of objects in a neutral domain (2 minutes). In learning phase 1 the participants were provided with the static versions of the dynamic and interactive visualizations accompanied by the instructional text (30 minutes). The information was either provided in a pre-integrated format or required learners to actively integrate it on their own. Then the learners took post-test 1 (20 minutes), followed by learning phase 2, in which the participants explored the dynamic and interactive visualizations without instructional guidance (15 minutes). Finally, the learners took post-test 2 (40 minutes). All participants had to spend the same time on the tasks.

3. RESULTS

With regard to the pre-test there were no statistically significant differences between the groups for any of the test categories. The results of the post-tests are presented in the following. Table 1 shows the means and the standard deviations for the three types of questions: textual-graphical, graphical-textual, and graphical-graphical. Table 2 shows the results of a multivariate (Wilks-Lambda) and univariate two-way analyses of variance with repeated measures on the factor *time of assessment*.

The analyses of variance revealed a significant effect of *information integration* for those test questions which addressed transformations from graphical to textual representations. Learners with active integration performed better than with pre-integrated information in all categories of both tests; however, with regard to the two other types of questions the comparisons failed to reach statistical significance. The factor *time of assessment* had a significant effect on the test categories graphical-textual and graphical-graphical as well as across all types of questions. However, there were no interaction effects indicating that learners of both groups improved their knowledge during the exploration of the dynamic and interactive visualizations to approximately the same degree.

D. BODEMER

Additionally performed *t*-tests revealed that, on average, learners with active integration already achieved better learning outcomes after the first learning phase. Against the expectations, these differences between the groups slightly diminished in the second assessment after learning phase 2.

Table 1: Relative solution frequencies and standard deviations in both post-tests for the different questions.

Information integration		textual-graphical		graphical-textual		graphical-graphic.	
		Test 1	Test 2	Test 1	Test 2	Test 1	Test 2
Pre-integrated	M	.74	.71	.21	.40	.55	.66
	SD	.26	.28	.28	.26	.26	.28
Actively integrated	M	.84	.78	.37	.52	.67	.69
	SD	.24	.26	.26	.23	.29	.22
Overall	M	.79	.74	.29	.46	.61	.67
	SD	.25	.27	.28	.25	.28	.25

Table 2: The results of the multivariate and univariate two-way analyses of variance.

Source of variance	Dependent variable	df	F
Between subjects			
Information integration	Across all types of questions	3, 44	1.48
	textual-graphical	1, 46	1.83
	graphical-textual	1, 46	4.32*
	graphical-graphical	1, 46	1.07
Within subjects			
Time of assessment	Across all types of questions	3, 44	10.05**
	textual-graphical	1, 46	1.48
	graphical-textual	1, 46	27.91**
	graphical-graphical	1, 46	4.05*
Time of assessment x Information integration	Across all types of questions	3, 44	.56
	textual-graphical	1, 46	.13
	graphical-textual	1, 46	.39
	graphical-graphical	1, 46	1.51

Note: * $p < .05$, ** $p < .01$

4. DISCUSSION

This paper investigated the benefit of an instructional support method to support learning with dynamic simulations in multimedia learning environments. Learners were encouraged to interactively and externally relate different static sources of information to each other before exploring dynamic simulations. In an experimental study the active integration of multiple representations was compared to the presentation of information in a pre-integrated format as suggested by Chandler and Sweller (1991, 1992) and Mayer (1997, 2001). The application domain was

ACTIVE INTEGRATION OF MULTIPLE REPRESENTATIONS

mechanics. It was hypothesized that learners who initially integrate multiple representations actively achieve better learning outcomes as found by Bodemer et al. (in press) for the domain of statistics.

The results largely confirmed that encouraging learners to actively integrate symbolic and static representations during multimedia learning can improve learning. Moreover, it shows that active integration of information – compared to the presentation of information in a pre-integrated format – can lead to the acquisition of knowledge already during learning with static symbolic and pictorial representations, and not only in combination with dynamic and interactive visualizations.

Contrary to expectations learners who actively integrated different representations were not able to improve comparatively more during simulation-based discovery learning. This may be due to the relatively low amount of additional information provided by the dynamic and interactive visualizations compared to their static versions. The static graphs already contained dynamic information by representing time on one axis. Ainsworth and van Labeke (2003) state that dynamic representations that express the relation between a variable and time do not contain more information than the same representation in a static form. Except for the illustration of the car with the corresponding velocity and acceleration vectors this applies to the dynamics of the simulation used in this study. However, the simulations contained additional information by providing the possibility to change variables interactively. But the number of changing options was very limited compared to the dynamic and interactive visualizations used by Bodemer et al. (in press).

The results differed with respect to the codalities of the test items. It appeared, that not only the retrieval cue codalities have to be considered (cf. Brünken, Steinbacher, Schnotz & Leutner, 2001); but also the codality of the learners' response effects the test result. Active integration of information was particularly helpful for answering questions that required transformations from graphical to textual representations.

Future research should consider the different codalities of test items as well as differences of visualizations and simulations with respect to the dynamics and the interactivity. Moreover, the learners' prior knowledge and the complexity of the learning task have to be accurately analyzed in further studies because they seem to significantly affect the use of actively integrating multiple representations.

AFFILIATION

Daniel Bodemer
Knowledge Media Research Center
Konrad-Adenauer-Str. 40, 72072 Tübingen, Germany
+49 7071 979-222
d.bodemer@iwm-kmrc.de

D. BODEMER

REFERENCES

- Ainsworth, S. (1999). The functions of multiple representations. *Computers and Education*, 33, 131-152.
- Ainsworth, S., Bibby, P. A., & Wood, D. J. (2002). Examining the effects of different multiple representational systems in learning primary mathematics. *Journal of the Learning Sciences*, 11(1), 25-62.
- Ainsworth, S. & van Labeke, N. (in press). Multiple forms of dynamic representation. *Learning and Instruction*.
- Blaschke, K., & Heuer, D. (2000). Dynamik-Lernen mit multimedial-experimentell unterstütztem Werkstatt-Unterricht [Learning dynamics in multimedia projects]. *Physik in der Schule*, 38(2), 1-6.
- Bodemer, D., Ploetzner, R., Feuerlein, I. & Spada, H. (in press). The active integration of information during learning with dynamic and interactive visualizations. *Learning and Instruction*.
- Brünken, R., Steinbacher, S., Schnotz, W., & Leutner, D. (2001). Mentale Modelle und Effekte der Präsentations- und Abrufkodierbarkeit beim Lernen mit Multimedia [Mental models and the effects of presentation and retrieval mode in multimedia learning]. *Zeitschrift für Pädagogische Psychologie*, 15, 15-27.
- Chandler, P., & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction*, 8(4), 293-332.
- Chandler, P., & Sweller, J. (1992). The split-attention effect as a factor in the design of instruction. *British Journal of Educational Psychology*, 62, 233-246.
- de Jong, T., & van Joolingen, W. R. (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research*, 68(2), 179-201.
- Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive Science*, 7, 155-170.
- Gentner, D., & Markman, A. B. (1997). Structure mapping in analogy and similarity. *American Psychologist*, 52(1), 45-56.
- Kalyuga, S., Chandler, P., & Sweller, J. (1999). Managing split-attention and redundancy in multimedia instruction. *Applied Cognitive Psychology*, 13, 351-371.
- Kozma, R. (2003). The material features of multiple representations and their cognitive and social affordances for science understanding. *Learning and Instruction*, 13(2), 205-226.
- Kozma, R.B., Russell, J., Jones, T., Marx, N., & Davis, J. (1996). The use of multiple, linked representations to facilitate science understanding. In S. Vosniadou, E. De Corte, R. Glaser & H. Mandl (Eds.), *International perspectives on the design of technology supported learning environments* (pp. 41-61). Hillsdale, NJ: Erlbaum.
- Larkin, J.H., & Simon, H.A. (1987). Why a diagram is (sometimes) worth ten thousands words. *Cognitive Science*, 11, 65-99.
- Leutner, D. (1993). Guided discovery learning with computer-based simulation games: effects of adaptive and non-adaptive instructional support. *Learning and Instruction*, 3, 113-132.
- Lowe, R. K. (1999). Extracting information from an animation during complex visual learning. *European Journal of Psychology of Education*, 14(2), 225-244.
- Lowe, R. K. (2003). Animation and learning: Selective processing of information in dynamic graphics. *Learning and Instruction*, 13(2), 157-176.
- Mayer, R. E. (1997). Multimedia learning: Are we asking the right questions? *Educational Psychologist*, 32(1), 1-19.
- Mayer, R. E. (2001). *Multimedia learning*. New York, NY: Cambridge University Press.
- Njoo, M., & de Jong, T. (1993). Supporting exploratory learning by offering structured overviews of hypotheses. In D. M. Towne & T. de Jong & H. Spada (Eds.), *Simulation-based experiential learning* (pp. 207-223). Berlin: Springer Publishers.
- Ploetzner, R., Bodemer, D., & Feuerlein, I. (2001). Facilitating the mental integration of multiple sources of information in multimedia learning environments. In C. Montgomerie & J. Viteli (Eds.), *Proceedings of the World Conference on Educational Multimedia, Hypermedia & Telecommunications* (pp. 1501-1506). Norfolk, VA: Association for the Advancement of Computing in Education.
- Reigeluth, C. M., & Schwartz, E. (1989). An instructional theory for the design of computer-based simulations. *Journal of Computer-Based Instruction*, 16(1), 1-10.
- Reimann, P. (1991). Detecting functional relations in a computerized discovery environment. *Learning and Instruction*, 1, 45-65.

ACTIVE INTEGRATION OF MULTIPLE REPRESENTATIONS

- Rieber, L. P., Tzeng, S.-C. & Tribble, K. (in press). Discovery learning, representation, and explanation within a computer-based simulation: Finding the right mix. *Learning and Instruction*.
- Schauble, L., Glaser, R., Raghavan, K., & Reiner, M. (1991). Causal models and experimentation strategies in scientific reasoning. *The Journal of the Learning Sciences*, 1, 201-239.
- Schnotz, W., & Bannert, M. (1999). Einflüsse der Visualisierungsform auf die Konstruktion mentaler Modelle beim Text- und Bildverstehen [Influence of the type of visualization on the construction of mental models during picture and text comprehension]. *Zeitschrift für Experimentelle Psychologie*, 46(3), 217-236.
- Schnotz, W., & Bannert, M. (2003). Construction and interference in learning from multiple representation. *Learning and Instruction*, 13(2), 141-156.
- Schnotz, W., Boeckheler, J., & Grzondziel, H. (1999). Individual and co-operative learning with interactive animated pictures. *European Journal of Psychology of Education*, 14(2), 245-265.
- Seufert, T. (2003). Supporting coherence formation in learning from multiple representations. *Learning and Instruction*, 13(2), 227-237.
- Swaak, J., van Joolingen, W. R., & de Jong, T. (1998). Supporting simulation-based learning: The effects of model progression and assignments on definitional and intuitive knowledge. *Learning and Instruction*, 8(3), 235-252.
- Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12, 257-285.
- Sweller, J., van Merriënboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, 10(3), 251-296.
- Tarmizi, R. A., & Sweller, J. (1988). Guidance during mathematical problem solving. *Journal of Educational Psychology*, 80(4), 424-436.
- van Joolingen, W. R. & de Jong, T. (1991). Supporting hypothesis generation by learners exploring an interactive computer simulation. *Instructional Science*, 20(5-6), 389-404.