The mirror-neuron system and observational learning: Implications for the effectiveness of dynamic visualizations.

Citation for published version (APA):

Van Gog, T., Paas, F., Marcus, N., Ayres, P., & Sweller, J. (2009). The mirror-neuron system and observational learning: Implications for the effectiveness of dynamic visualizations. *Educational Psychology Review*, *21*(1), 21-30. https://doi.org/10.1007/s10648-008-9094-3

DOI:
10.1007/s10648-008-9094-3

Document status and date:
Published: 01/03/2009

Document Version:
Peer reviewed version

This is a pre-print of: Van Gog, T., Paas, F., Marcus, N., Ayres, P., & Sweller, J. (2009). The mirror-neuron system and observational learning: Implications for the effectiveness of dynamic visualizations. *Educational Psychology Review*, *21*, 21-30.

The original publication is available at www.springerlink.co

The Mirror-Neuron System and Observational Learning: Implications for the Effectiveness of Dynamic Visualizations

Tamara van Gog[1,2,*], Fred Paas[1,2,3], Nadine Marcus[4], Paul Ayres[4], and John Sweller[4]

[1]Centre for Learning Sciences and Technologies (CELSTEC),

[2]Netherlands Laboratory of Lifelong Learning (NeLLL)

Open University of the Netherlands

[3]Institute of Psychology, Erasmus University Rotterdam, the Netherlands

[4]University of New South Wales, Sydney, Australia

*Correspondence concerning this article should be addressed to Tamara van Gog, Open University of the Netherlands, Centre for Learning Sciences and Technologies (CELSTEC), P.O. Box 2960, 6401 DL, Heerlen, The Netherlands. Phone: +31 45 5762276, Fax: + 31 45 5762907, E-mail: tamara.vangog@ou.nl.

Abstract

Learning by observing and imitating others, has long been recognized as constituting a powerful learning strategy for humans. Recent findings from neuroscience research, more specifically, on the mirror-neuron system, begin to provide insight into the neural bases of learning by observation and imitation. These findings are discussed here, along with their potential consequences for the design of instruction, focusing in particular on the effectiveness of dynamic vs. static visualizations.

The Mirror-Neuron System and Observational Learning: Implications for the Effectiveness of Dynamic Visualizations

Observational learning is considered one of the most basic and powerful mechanisms by which people learn (Bandura, 1986). Indeed, we may have *evolved* to observe and imitate other people (see Sweller & Sweller, 2006). Cognitive load theory (CLT) argues that because of the way human cognitive architecture is organized, learning by observing and/or imitating[1] what other people do, say, or write, is a much more effective and efficient way of acquiring knowledge than trying to devise this knowledge by ourselves (Paas, Renkl, & Sweller, 2003, 2004; Sweller, 1988, 2004; Sweller & Sweller, 2006; Sweller, Van Merriënboer, & Paas, 1998; Van Merriënboer & Sweller, 2005).

Many educational programs advocate that problem-solving skills are acquired best by having learners solve many problems. Indeed, when faced with new problems for which there are no known solutions or models available, there is no alternative to problem solving. However, as argued by CLT, in all other cases observational learning is much more effective and efficient, and should be implemented where possible. A large body of empirical research has confirmed that learning from "expert"[2] models, either by observing them solving problems "live" or on video (i.e., modeling examples), or by studying a written account of their problem-solving process (i.e., worked examples), is very effective for acquiring both motor and cognitive skills, and is more effective for novice learners than learning by solving the equivalent problems (e.g., Braaksma, Rijlaarsdam, Van den Bergh, & Van Hout-Wolters, 2004; Cooper & Sweller, 1987; Kitsantas, Zimmermann, & Cleary, 2000; Paas, 1992; Paas & Van Merriënboer, 1994; Sweller & Cooper, 1985; Van Gog, Paas, & Van Merriënboer, 2006). However, the effectiveness of learning from examples does seem to depend on the expertise of the learner: Once a learner knows how to perform the task, the examples no longer contribute to learning, and may even hamper it (i.e., the "expertise-reversal effect"; Kalyuga, Ayres, Chandler, & Sweller, 2003).

The Mirror Neuron System

The discovery of the mirror-neuron system is a major neuroscience finding relevant to observational learning. This system is thought to play an important role in the understanding of actions made by others, and may be responsible for our ability to learn by observing and imitating others. It was discovered, more or less by accident, in monkeys in the early 1990's. Researchers studying cortical activation in monkeys that had to grasp objects from a box, noted incidentally that activation also occurred when the monkeys observed the experimenters grasping the objects (Di Pellegrino, Fadiga, Fogassi, Gallese, & Rizzolatti, 1992). Much of the evidence for the mirror neuron system in monkeys comes from single neuron recordings. As this technique has (for obvious reasons) not been used in humans, there is no *direct* evidence that a mirror neuron system also exists in humans (Rizzolatti & Craighero, 2004). However, numerous studies using Transcranial Magnetic Stimulation or brain imaging techniques have provided convincing evidence that the human motor system also has mirroring capacity, and is activated by observing motor actions made by others (for a review see Rizzolatti & Craighero, 2004). That is, the same cortical circuits that are involved in executing an action oneself, also respond to observing someone else executing that action. Moreover, this seems to prime the execution of similar actions, which suggests that the mirror-neuron system mediates *imitation*, by priming (i.e., preparing the brain for) execution of the same action (Buccino et al., 2004; Craighero, Bello, Fadiga, & Rizzolatti, 2002; Iacoboni et al., 1999; Vogt, Taylor, & Hopkins, 2003). It should be noted that imitation seems to be a capacity of the human mirror neuron system that is absent in monkeys (Rizzolati, 2005). A crucial difference between the mirror neuron system of monkeys and humans seems to be that in monkeys, the mirror neuron system is only activated by goal directed actions. Although many of the studies on the human mirror neuron system also involve goal directed movements like observing the grasping of an object (e.g., Craighero et al., 2002) or playing a guitar chord (Buccino et al., 2004), there are indications that it is also activated by intransitive (meaningless) movements (Fadiga, Fogassi, Pavesi, & Rizzolatti, 1995). It is assumed that monkeys can therefore only understand the goal of an action and try to copy it, but they presumably cannot encode the details of the action with which the goal is achieved. Humans can encode *how* the goal is achieved, thereby enabling imitation (Rizzolatti, 2005).

In addition, the mirror neuron system seems to play a role in *understanding* action, that is, in inferring intentions of actions (Rizzolatti, 2005; Rizzolatti & Craighero, 2004). Understanding action enables learning by observing not only what another individual is doing, but also why s/he is doing it. In the educational literature, this facet of understanding is assumed critical for attaining transfer, that is, application of what has been learned in new tasks or contexts (see e.g., Detterman & Sternberg, 1993; in the context of example-based learning, see Van Gog, Paas, & Van Merriënboer, 2004). Even very young children seem capable of understanding intentions: a study by Gergely, Bekkering, and Király (2002), showed that babies do not necessarily imitate an observed motor action, but interpret this action in terms of its context and goals, and may choose another way of achieving the same goal (i.e., rational imitation).

For some time, it was thought that the mirror neuron system was only activated when observing a real human body (part) executing an action, and not when the action was conducted by some other agent, such as a robot arm for example (Tai, Scherfler, Brooks, Sawamoto, & Castiello, 2004). However, recent evidence suggests that the *goal* of the observed action is more important for activation than the presence, for example, of a human vs. a robotic hand (Gazzola, Rizzolatti, Wicker, & Keysers, 2007).

Interestingly, there are indications that the same brain areas involved in the execution and observation of motor actions also become active when people listen to sentences that describe the performance of human actions using hands, mouths, or legs (Tettamanti et al., 2005), or when people imagine performing an action without actual movement (Grèzes & Decety, 1996). Hurley (2008) proposed that the processes of motor control, mirroring, and mental simulation (or imagination) rely on shared neural circuits.

Instructional Design Consequences

Motor Skills

It should be clear from the above that one of the areas where the findings regarding the mirror-neuron system might contribute to instructional design, is in observational learning of motor skills. Specifically, we propose here that the above neuroscience findings might partially explain an open question in the instructional design community, that is, why dynamic visualizations are sometimes more and sometimes less effective than static visualizations.

Dynamic visualizations such as video or animation have become a popular means of providing instruction (Ayres & Paas, 2007a; Lowe & Schnotz, 2008; Mayer, 2005; Schnotz & Lowe, 2003). It has been suggested that dynamic visualizations should enhance learning by assisting students to perceive the temporal changes or movement in a system, whereas learning from static visualizations requires students to mentally infer these temporal changes. Learning by inferring temporal changes is believed to require more cognitive effort than perceiving temporal changes (see e.g., Hegarty, Kriz, & Cate, 2003). However, it has also been argued that the transient nature of dynamic visualizations challenges the assumption that the mental inferences of movement or change required by static visualizations are more effort demanding than perceiving this change as dynamic visualizations (see e.g., Ayres & Paas, 2007b). The limitations of working memory, both regarding capacity and time (Barrouillet & Camos, 2007; Cowan, 2001; Miller, 1956), pose an immediate problem when dealing with transient information. Students have to process currently visible information, remember previously presented information, and relate and integrate current with previous information in order to comprehend the visualization, which might cause a temporal split-attention effect (e.g., Ayres & Sweller, 2005). These activities can be expected to impose a high working memory load that may compromise comprehension because the continuing flow of information into a limited capacity, limited duration working memory may leave very little time and/or capacity to keep in mind, relate, and integrate information. Hence, information presented during earlier phases of a dynamic visualization may be lost before it can be integrated with current information. In contrast, static visuals do not pose a similar problem of information transience because they can be revisited on multiple occasions. Just replaying dynamic visualizations repeatedly also allows revisiting, but may do little to ameliorate the temporal split-attention problem since split-attention will occur on each iteration.

This high working memory load might therefore explain why, despite their popularity and the fact that dynamic visualizations seem an intuitively superior instructional format for representing change over time than static graphics, the superiority of dynamic over static visualizations has not always been demonstrated empirically. Tversky, Morrison, and Betrancourt (2002) explained this failure in terms of the congruency and apprehension principles. According to the congruency principle, dynamic visualizations may only be more effective than static ones when their representation of the content is congruent with the internal representation students need to acquire the relevant knowledge. For example, Tversky et al. indicated that because routes to be traversed are perceived as a series of turns, an effective animation should be based on turns. The apprehension principle states that dynamic visualizations may only be more effective when they allow for easier perception and understanding of the structure and content than static representations. For example, if a mechanical process is depicted at its natural speed, this speed may be far too low (e.g., the working of a pendulum clock; Fischer, Lowe, & Schwan, in press) or far too high (e.g., the working of a four-stroke engine; Meyer, Schnotz, & Rasch, 2008), to readily perceive the relevant changes or procedures. In a recent meta-analysis, Höffler and Leutner (2007) drew the more positive conclusion that dynamic visualizations were more effective than static visualizations. In particular, the effect was greater when the animation was representational (as opposed to decorational), when it was highly realistic, and when procedural-motor knowledge was to be acquired.

We suggest that the mixed findings of research into instructional visualizations can, at least in part, be explained by neuroscience research on the mirror-neuron system. The bulk of dynamic visualizations has focused on natural processes such as how lightning develops or how the tides work, on technical systems such as the functioning of a bicycle pump or a chemical distillation process, or on abstract processes such as probability calculation (see Lowe & Schnotz, 2008). However, research on the mirror-neuron system suggests that dynamic visualizations may be most effective for learning tasks that involve human movement, because such visualizations automatically trigger an effortless process of embodied simulation by the mirror-neuron system, which primes the execution of similar actions. That is, due to activation of the mirror-neuron system, the information processing difficulties related to the transient nature of information in dynamic visualizations, may not occur or may be overcome. In this case, dynamic visualizations should be most effective for learning tasks such as surgical procedures, assembly tasks, origami, or sports, but much less effective for tasks that involve non-human movement such as mechanical, biological, chemical, or abstract processes for which they are nowadays most frequently used.

The mirror-neuron system is a system that humans (and, indeed, other primates) have evolved to use over many generations. It can be linked to Geary's (2007) concept of evolutionary primary knowledge which is knowledge we have evolved to acquire. Such knowledge can be acquired easily, quickly and with relatively little effort. Our evolved ability to acquire knowledge of human movement may explain why we can readily obtain such knowledge by observing human movement. In contrast, we may not have evolved to translate a series of static diagrams into human movement. That skill may constitute an example of evolutionary secondary knowledge that is culturally important but for which there may be no explicit neural structures available to facilitate the acquisition of the knowledge. Accordingly, dynamic may be superior to static diagrams when dealing with human movement but not necessarily when dealing with non-human movement.

Indeed, an advantage of dynamic over static visualizations has been shown for tasks involving human movement, for example in knot-tying, assembly, first-aid procedures, puzzle construction, or origami tasks (see e.g., Arguel & Jamet, in press; Ayres, Marcus, Chan, & Qian, in press; Park & Hopkins, 1993; Wetzel, Radtke, & Stern, 1994; Wong et al., in press). Tasks involving human movement also seem to be most completely consistent with Tversky et al.'s (2002) congruency and apprehension principles, which are claimed to determine the effectiveness of dynamic visualizations. Dynamic visualizations of human movement tasks are also more in line than non-human movement tasks with the learning goals and tests required of a learner, who often must learn to perform the observed task (i.e., imitation). In contrast, non-human movement tasks most often use conceptual learning and apply written knowledge tests. Learners are not typically requested to 'act like a clock' or 'enact lightning' after watching a clock or lightning animation. Thus, the congruency and apprehension principles may apply much more directly to human movement than non-human movement tasks. This difference may be important: using a motor task, Jeon and Branson (1981) showed that learners in a dynamic condition performed the task better after the learning phase than learners presented static illustrations with written or spoken text, but did not do better on a written test. The findings by Höffler and Leutner (2007) also show that the beneficial effect of dynamic over static visualizations is greater when procedural-motor knowledge has to be acquired.

Even though Höffler and Leutner's (2007) meta-analysis suggests that realism is important, the finding that the goal of the action seems to be most important for the activation of the mirror neuron system (Gazzola et al., 2007), strongly suggests that dynamic visualizations do not have to be restricted to videos of humans performing a task. They might also include computer animations in which humans are not directly depicted, as long as the goal-directed movement is seen as being related to human movement. For example, an option might be to have an animated agent (cf. robotic agent) perform the movement, or, as in the study by Wong et al. (in press), to show the movement without any agent explicitly depicted but rather, implicitly depicted by the movement of objects (Wong et al. used an origami task in which the paper folding movement was shown but the hands executing the movement were not visible).

Cognitive Skills

The research reported above suggests that the mirror-neuron system plays a key role in observational learning of motor tasks. It is as yet unclear whether non-motor neurons, that is, neurons involved in the execution of cognitive tasks, also have mirroring capacity. A lot of educational research has demonstrated the effectiveness of observational learning for cognitive tasks (e.g., mathematics). However, it is unclear whether a mechanism similar to the motor mirror-neuron system is at work in observational learning of those cognitive tasks. There are some interesting parallels and links between findings on cognitive and motor tasks though, that suggest this might be an interesting issue to explore in future research.

Firstly, many complex tasks that have a motor component, also have a cognitive component. For example, Ayres et al. (in press) recently found that the benefits of dynamic visualizations over statics for the learning of motor tasks extended to both transfer (performing the motor task in reverse order) and related cognitive tasks (determining based on a screen shot what the previous or next move was).

Secondly, the mirror-neuron system has also been proposed to play a role in social cognition in a more general sense, for example, in understanding social intentions (theory of mind; see e.g., Keysers & Gazzola, 2007). Interpreting actions of others in this manner, seems to go well beyond activating a similar motor program, and might therefore also play a role in observational learning of cognitive skills.

When it comes to purely cognitive skills (e.g., mathematics) an important difference between observational learning of motor skills and cognitive skills, is that cognitive “actions” are not readily observable. They need to be inferred from physical actions that follow from them, or need to be made explicit (e.g., by thinking aloud) in order to be “observed”. Instructional formats for observational learning of cognitive tasks often have models think aloud (live or video-based models) or provide a written account of cognitive actions (worked examples). As mentioned before, (Tettamanti et al., 2005) found that the mirror neuron system was also activated by listening to sentences describing motor actions. An interesting question is whether a similar effect of listening to action sentences might also apply to cognitive tasks, that is, could listening to sentences about an operation when solving a mathematics problem, prime the brain areas responsible for performing that operation oneself?

Concerning the findings regarding understanding actions, an interesting parallel in observational learning of cognitive skills is that to some extent, learners also seem to be able to interpret the intention of cognitive actions that have been made explicit in written form (cf. research on self-explaining worked examples; Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Renkl, 1997). However, it has also been argued and shown that for novice learners, having the example or model being explicit about the rationale underlying actions can benefit learning (Van Gog et al., 2004, 2006, 2008). In other words, this suggests that on cognitive tasks, the learner needs some prior knowledge that can act as a framework for interpreting the action.

This need for prior knowledge also seems to apply to imagining, or mental simulation of cognitive tasks, which provides another interesting parallel with motor tasks. Imagining motor actions seems to involve some of the same brain regions as performing or observing those actions (see Grèzes & Decety, 2001; Hurley, 2008). Educational research has shown that imagining problem-solving steps to be performed can be effective for learning cognitive tasks, but only once the required actions form part of the learners' repertoire (i.e., not for novices, but for advanced learners; Cooper, Tindall-Ford, Chandler, & Sweller, 2001; Leahy & Sweller, 2005, 2008). This role of prior knowledge may reflect a difference between cognitive and motor tasks, stemming from the difference between biologically primary (many motor tasks) and biologically secondary (required for most cognitive tasks) knowledge (Geary, 2007). However, it should be kept in mind that the tasks used in neuroscience research thus far have been relatively simple (e.g., grasping an object), so it may also be the case that on more complex motor tasks, prior knowledge is also required before intentions can be inferred or actions can be rehearsed by imagining rather than performing them.

Discussion

There is currently an upsurge of interest in relating neuroscience research to education (see e.g., De Jong et al., 2008; Goswami, 2004; Katzir & Paré-Blagoev, 2006; OECD, 2007; Stern, Grabner, & Schumacher, 2006). However, with the exception of research on (second) language learning and mathematics learning and associated learning disabilities such as dyslexia and dyscalculia (see Katzir & Paré-Blagoev, 2006), neuroscience has not yet really been able to make concrete contributions to educational research, and interdisciplinary research is rare, although there are several other areas where joint research ventures might prove possible and fruitful (see De Jong et al., 2008), some of which have been discussed here.

We have argued that the mirror-neuron system may provide a neuroscience base for some educational procedures and hypotheses associated with the design of dynamic and static visualizations. The mixed findings concerning the effectiveness of instructional animations have been a puzzle for some time. At least a partial solution to that puzzle may be provided by the suggestion that the mirror neuron system assists in acquiring motor skills by observation, thus altering the effectiveness of dynamic compared to static visualizations. However, this remains an hypothesis to be tested, for which interdisciplinary research is required. Such research might also shed light on the relation between the mirror neuron system and working memory. We assume that visualizations depicting human movement may trigger an automatic and therefore effortless process of embodied simulation by the mirror-neuron system. From a cognitive load perspective, this might benefit learning by leaving more working memory capacity available for processes such as elaboration or reflection on intentions of actions, compared to static visualizations. However, we do not know whether and how the mirror neuron system and working memory interact at a neural level (indeed, working memory itself is a much debated construct in neuroscience, see e.g. Osaka, Logie, & D'Esposito, 2007).

Another question where interdisciplinary research may provide interesting findings concerns whether the mirror-neuron system plays a role in observational learning of cognitive skills. Even though there seem to be some interesting parallels between observational learning of motor skills and cognitive skills in the educational literature, without further research, the potential role of mirror neurons for cognitive skills remains speculative.

It should be noted that we do not mean to imply here that dynamic visualizations should only be used for tasks involving human movement. For tasks that do not involve human movement, instructional interventions may improve the effectiveness of dynamic compared to static visualizations by reducing ineffective working memory load imposed by characteristics of the animations, such as transience. Such interventions could be, for example, self-pacing, segmenting, cueing, or changing the speed of presentation, although further research is necessary to arrive at clear design guidelines (see e.g., Lowe & Schnotz, 2007; Ayres & Paas, 2007a; Wouters, Paas, & Van Merriënboer, in press).

We also do not mean to imply that dynamic visualizations for human movement tasks could not be further improved by instructional interventions. For example, findings by Arguel & Jamet (in press) on learning a first aid procedure show that even though dynamic visualizations were more effective than statics, their effectiveness could be further improved by adding static pictures of key actions to the dynamic visualization. In addition, when an expert can perform a task so rapidly that it becomes difficult for a novice to observe the sequence of movements, influencing the speed of the dynamic visualization may help. In sum, further research on how to improve the effectiveness of different kinds of dynamic visualizations is still required, but neuroscience findings on the mirror neuron system may help us understand why some dynamic visualizations have proven more effective than others.

References

Arguel, A., & Jamet, E. (in press). Using video and static pictures to improve learning of procedural contents *Computers in Human Behavior*.

Ayres, P., Marcus, N., Chan, C., & Qian, N. (in press). Learning hand manipulative tasks: When instructional animations are superior to equivalent static representations. *Computers in Human Behavior*.

Ayres, P., & Paas, F. (Eds.) (2007a). A cognitive load approach to the learning effectiveness of instructional animation [special issue]. *Applied Cognitive Psychology*, *21*(6).

Ayres, P., & Paas, F. (2007b). Making instructional animations more effective: A cognitive load approach. *Applied Cognitive Psychology*, *21*, 695-700.

Ayres, P., & Sweller, J. (2005). The split-attention principle in multimedia learning. In R. E. Mayer (Ed.), *The Cambridge Handbook of Multimedia Learning* (pp. 135-146). New York: Cambridge University Press.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice Hall.

Barouillet, P., & Camos, V. (2007). The time-based resource-sharing model of working memory. In N. Osaka, R. H. Logie, & M. D'Esposito (Eds.), *The cognitive neuroscience of working memory* (pp. 59-80). Oxford: Oxford University Press.

Braaksma, M., Rijlaarsdam, G. C. W., Van den Bergh, H., & Van Hout-Wolters, B. A. M. (2004). Observational learning and its effects on the orchestration of the writing process. *Cognition & Instruction*, *22*, 1-36.

Buccino, G., Vogt, S., Ritzl, A., Fink, G., Zilles, K., Freund, H., & Rizzolatti, G. (2004). Neural circuits underlying imitation learning of hand actions: An event-related fMRI study. *Neuron*, *42*, 323-334.

Chi, M. T. H., Bassok, M., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Selfexplanations: How students study and use examples in learning to solve problems. *Cognitive Science*, *13*, 145-182.

Chi, M. T. H., Glaser, R., & Farr, M. (Eds.). (1988). *The nature of expertise*. Hillsdale, NJ: Erlbaum.

Cooper, G., & Sweller, J. (1987). The effects of schema acquisition and rule automation on mathematical problem-solving transfer. *Journal of Educational Psychology*, *79,* 347-362.

Cooper, G., Tindall-Ford, S., Chandler, P., & Sweller, J. (2001). Learning by imagining. *Journal of Experimental Psychology: Applied*, *7*, 68-82.

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral & Brain Sciences*, *24*, 87-114.

Craighero, L., Bello, A., Fadiga, L., & Rizzolatti, G. (2002). Hand action preparation influences the responses to hand pictures. *Neuropsychologia*, *40*, 492-502.

De Jong, T., Van Gog, T., Jenks, K., Manlove, S., Van Hell, J., Jolles, J., et al. (2008). Explorations in learning and the brain: On the potential of cognitive neuroscience for education. Berlin: Springer. Also available (downloaded July 28, 2008) from www.nwo.nl/files.nsf/pages/NWOA_7GFD3Y/ $file/Explorations_in_Learning_and_the_Brain.pdf

Detterman, D. K., & Sternberg, R. J. (Eds.) (1993). *Transfer on trial: Intelligence, cognition, and instruction*. Norwood, NJ: Ablex Publishing.

Di Pellegrino, G., Fadiga, L., Fogassi, L., Gallese, V., & Rizzolatti, G. (1992). Understanding motor events: A neurophysiological study. *Experimental Brain Research*, *91*, 176-180.

Ericsson, K. A., & Lehmann, A. C. (1996). Expert and exceptional performance: Evidence for maximal adaptation to task constraints. *Annual Review of Psychology*, *47*, 273-305.

Fadiga, L., Fogassi, L., Pavesi, G., & Rizzolatti, G. (1995). Motor facilitation during action observation: A magnetic stimulation study. *Journal of Neurophysiology*, *73*,2608–2611.

Fischer, S., Lowe, R. K., & Schwan, S. (in press). Effects of presentation speed of a dynamic visualization on the understanding of a mechanical system. *Applied Cognitive Psychology*.

Gazzola, V., Rizzolatti, G., Wicker, B., & Keysers, C. (2007). The anthropomorphic brain: The mirror neuron system responds to human and robotic actions. *NeuroImage*, *35*, 1674-1684.

Geary, D. (2007). Educating the evolved mind: Conceptual foundations for an evolutionary educational psychology. In J. S. Carlson & J. R. Levin (Eds.), *Psychological perspectives on contemporary educational issues* (pp. 1-99). Greenwich, CT: Information Age Publishing.

Gergely, G., Bekkering, H., & Király, I. (2002). Rational imitation in preverbal infants: Babies may opt for a simpler way to turn on a light after watching an adult do it. *Nature*, *415*, 755.

Goswami, U. (2004). Neuroscience and education. *British Journal of Educational Psychology*, *74*, 1-14.

Grèzes, J., & Decety, J. (2001). Functional anatomy of execution, mental simulation, observation, and verb generation of actions: A meta-analysis. *Human Brain Mapping*, *12*, 1-19.

Hegarty, M., Kriz, S., & Cate, C. (2003). The roles of mental animations and external animations in understanding mechanical systems. *Cognition and Instruction*, *21*, 325-360.

Höffler, T. N., & Leutner, D. (2007). Instructional animation versus static pictures: A meta-analysis. *Learning and Instruction*, *17*, 722-738.

Hurley, S. (2008). The shared circuits model (SCM): How control, mirroring, and simulation can enable imitation, deliberation, and mindreading. *Behavioral and Brain Sciences*, *31*, 1-58.

Leahy, W., & Sweller, J. (2005). Interactions among the imagination, expertise reversal and element interactivity effects. *Journal of Experimental Psychology: Applied*, *11*, 266-276.

Leahy, W., & Sweller, J. (2008). The imagination effect increases with an increased intrinsic cognitive load. *Applied Cognitive Psychology*, *22*, 273-283.

Iacoboni, M., Woods, R., Brass, M., Bekkering, H., Mazziotta, J., & Rizzolatti, G. (1999). Cortical mechanisms of human imitation. *Science*, *286*, 2526-2528.

Jeon, U. H., & Branson, R. K. (1981). Performance and simulated performance test results as a function of instruction by still and motion visuals. *Journal of Educational Technology Systems*, *10*, 33-44.

Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist*, *38*, 23-32.

Katzir, T., & Paré-Blagoev, J. (2006). Applying cognitive neuroscience research to education: The case of literacy. *Educational Psychologist*, *41*, 53-74.

Keysers, C., & Gazzola, V. (2007). Integrating simulation and theory of mind: From self to social cognition. *Trends in Cognitive Sciences*, *11*, 194-196.

Kitsantas, A., Zimmerman, B. J., & Cleary, T. (2000). The role of observation and emulation in the development of athletic self-regulation. *Journal of Educational Psychology*, *92* 811-817.

Lowe, R. K., & Schnotz, W. (Eds.) (2008). *Learning with animation: Research implications for design*. New York: Cambridge University Press.

Mayer, R. E. (Ed.) (2005). *The Cambridge handbook of multimedia learning*. New York:

Cambridge University Press.

Meyer, K., Rasch, T., & Schnotz, W. (2008) *Effects of playing rate of animations on perceptual and cognitive processing*. Manuscript submitted for publication.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity to process information. *Psychological Review*, *63*, 81-97.

OECD (2007). *Understanding the brain: The birth of a learning science*. Paris: Office of Economic Cooperation and Development.

Osaka, N., Logie, R. H., & D'Esposito, M. (Eds.) (2007). *The cognitive neuroscience of working memory*. Oxford: Oxford University Press.

Paas, F. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive load approach. *Journal of Educational Psychology, 84*, 429-434.

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, *38,* 1-4.

Paas, F., Renkl, A., & Sweller, J. (2004). Cognitive load theory: Instructional implications of the interaction between information structures and cognitive architecture. *Instructional Science*, *32*, 1-8.

Paas, F., & Van Merriënboer, J. J. G. (1994). Variability of worked examples and transfer of geometrical problem-solving skills: A cognitive load approach. *Journal of Educational Psychology*, *86*, 122-133.

Park, O., & Hopkins, R. (1993). Instructional conditions for using dynamic visual displays: A review. *Instructional Science*, *21*, 427-449.

Renkl, A. (1997). Learning from worked-out examples: A study on individual differences. *Cognitive Science*, *21*, 1-29.

Rizzolatti, G. (2005). The mirror neuron system and its function in humans. *Anatomy and Embryology*, *210*, 419-421.

Rizzolatti, G., & Craighero, L. (2004). The mirror-neuron system. *Annual Review of Neuroscience*, *27*, 169-192.

Schnotz, W., & Lowe, R. K. (Eds.) (2003). External and internal representations in multimedia learning [special issue]. *Learning and Instruction*, *13*(2).

Stern, E., Grabner, R., & Schumacher, R. (2006). *Educational research and neurosciences - Expectations, evidence, research prospects*. Berlin: Federal Ministry of Education and Research.

Sweller, J. (1988). Cognitive load during problem-solving: Effects on learning. *Cognitive Science*, *12*, 257–285.

Sweller, J. (2004). Instructional design consequences of an analogy between evolution by natural selection and human cognitive architecture. *Instructional Science*, *32*, 9-31.

Sweller, J., & Cooper, G. A. (1985). The use of worked examples as a substitute for problem solving in learning algebra. *Cognition and Instruction*, *2*, 59-89.

Sweller, J., & Sweller, S. (2006). Natural information processing systems. *Evolutionary Psychology*, *4*, 434-458.

Sweller, J., Van Merriënboer, J. J. G., & Paas, F. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, *10*, 251–295.

Tai, Y., Scherfler, C., Brooks, D., Sawamoto, N., & Castiello, U. (2004). The human premotor cortex is "mirror" only for biological actions. *Current Biology*, *14*, 117-120.

Tettamanti, M., Buccino, G., Saccuman, M. C., Gallese, V., Danna, M., Scifo, P. Fazio, F., Rizzolatti, G. Cappa, S., & Perani, D. (2005). Listening to action-related sentences activates fronto-parietal motor circuits. *Journal of Cognitive Neuroscience*, *17*, 273-281.

Tversky, B., Morrison, J. B., & Betrancourt, M. (2002). Animation: can it facilitate? *International Journal of Human-Computer Studies*, *57*, 247-262.

Van Gog, T., Paas, F., & Van Merriënboer, J. J. G. (2004). Process-oriented worked examples: Improving transfer performance through enhanced understanding. *Instructional Science*, *32*, 83-98.

Van Gog, T., Paas, F., & Van Merriënboer, J. J. G. (2006). Effects of process-oriented worked examples on troubleshooting transfer performance. *Learning and Instruction*, *16*, 154-164.

Van Gog, T., Paas, F., & Van Merriënboer, J. J. G. (2008). Effects of studying sequences of process-oriented and product-oriented worked examples on troubleshooting transfer efficiency. *Learning and Instruction*, *18*, 211-222.

Van Merriënboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review*, *17*, 147-177.

Vogt, S., Taylor, P., & Hopkins, B. (2003). Visuomotor priming by pictures of hand postures: perspective matters. *Neuropsychologia*, *41*, 941–951.

Wetzel, C. D., Radtke, P. H., & Stern, H. W. (1994). *Instructional effectiveness of video media*. Hillsdale, NJ: Erlbaum.

Wong, A., Marcus, N., Ayres, P., Smith, L., Cooper, G. A., Paas, F., & Sweller, J. (in press). Instructional animations can be superior to statics when learning human motor skills. *Computers in Human Behavior*.

Wouters, P., Paas, F., & Van Merriënboer, J. J. G. (in press). How to optimize learning from animated models? A review of guidelines based on cognitive load. *Review of Educational Research*.

Footnote

[1] The terms observational learning and imitation learning are often used interchangeably, but they may be distinguished in that learning may occur without imitation taking place, that is, we may learn by observing and generating inferences beyond the observation without actually imitating the observed model (Bandura, 1986). Because it is broader, we will use the term 'observational learning' throughout this article.

[2] It is important to define expertise here. Some authors define "experts" as being individuals who excel in a domain (Ericsson & Lehmann, 1996), others as individuals with extensive experience in a domain (Chi, Glaser, & Farr, 1988), but in educational research it is also often used to refer to individuals who can perform a particular task really well (e.g., as in the "expertise reversal effect"; Kalyuga, Ayres, Chandler, & Sweller, 2003). This can have important consequences for the effectiveness of models, because domain experts differ enormously from students in the amount of knowledge they have, in the way this knowledge is organized, and the extent to which experts have automated problem-solving procedures (Chi et al., 1988). Therefore, having domain experts as a model might not help students, because the knowledge gap is too large, whereas task experts might be effective models. The issue can be resolved by consistently using the term "expertise" in a relative rather than absolute sense. In this paper, the term "expertise" should be considered in terms of "levels of expertise" rather than absolute expertise. One instructional technique may facilitate expertise more than another because it increases knowledge more irrespective of the absolute level of expertise, and an expert can be someone with a higher level of expertise than the learner.