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

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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.

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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.

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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.