Educ Psychol Rev
DOI 10.1007/s10648-011-9179-2

REVIEW

An Evolutionary Upgrade of Cognitive Load Theory: Using the Human Motor System and Collaboration to Support the Learning of Complex Cognitive Tasks

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Abstract Cognitive load theory is intended to provide instructional strategies derived from experimental, cognitive load effects. Each effect is based on our knowledge of human cognitive architecture, primarily the limited capacity and duration of a human working memory. These limitations are ameliorated by changes in long-term memory associated with learning. Initially, cognitive load theory's view of human cognitive architecture was assumed to apply to all categories of information. Based on Geary's (*Educational Psychologist 43*, 179–195 2008; 2011) evolutionary account of educational psychology, this interpretation of human cognitive architecture requires amendment. Working memory limitations may be critical only when acquiring novel information based on culturally important knowledge that we have not specifically evolved to acquire. Cultural knowledge is known as biologically secondary information. Working memory limitations may have reduced significance when acquiring novel information that the human brain specifically has evolved to process, known as biologically primary information. If biologically primary information is less affected by working memory limitations than biologically secondary information, it may be advantageous to use primary information to assist in the acquisition of secondary information. In this article, we suggest that several cognitive load effects rely on biologically primary knowledge being used to facilitate the acquisition of biologically secondary knowledge. We indicate how incorporating an evolutionary view of human cognitive architecture can provide cognitive load researchers with novel perspectives of their findings and discuss some of the practical implications of this view.

Keywords Cognitive load theory · Human motor system · Collaborative learning · Evolutionary educational psychology · Complex cognitive tasks

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Published online: 06 September 2011

Cognitive load theory provides a theoretical framework dealing with *individual* information processing and learning (Paas *et al*. 2003a; 2004; Paas and Van Merriënboer 1994a; Sweller 1988, 2010; Sweller *et al*. 2011, 1998; Van Merriënboer and Sweller 2005). In recent years, that theoretical framework has increasingly relied on biological evolution (Sweller 2003, 2011a, b; Sweller and Sweller 2006) firstly, by treating biological evolution as an information processing theory and suggesting that human cognition processes information in an analogous fashion and secondly, by categorizing knowledge according to its evolutionary status.

Human cognitive architecture can be specified using similar structures and functions to biological evolution. This architecture consists of an effectively unlimited long-term memory intended to govern activity in the same way as a genome governs biological activity. Most of the information is acquired by long-term memory when reading what other people have written, listening to what other people say, and observing what other people do, in a manner that is analogous to the way in which a genome acquires information from other genomes during reproduction. While most information held in long-term memory is obtained from other people, that information must be initially created. Novel information is created during problem solving using a random generate and test process analogously to the way in which random mutation creates novel genomic information. That novel information is processed by a working memory that is limited in capacity to 4±1 elements of information (Cowan 2001; Baddeley 1986; Miller 1956) and duration to about 20 s (Peterson and Peterson 1959). Working memory processes new information from the environment in a similar way to the manner in which the epigenetic system processes novel, environmental information. The epigenetic system links the environment to a genome (Sweller and Sweller 2006).

The capacity and duration limits of working memory are far below the requirements of most substantive areas of human intellectual activity. Alone, working memory would only permit relatively trivial human cognitive activities. The relation between working memory and long-term memory resolves the problem (Ericsson and Kintsch 1995). The capacity and duration limits of working memory are eliminated when working memory deals with familiar information organized in long-term memory rather than unfamiliar information from the environment. Long-term memory contains cognitive schemas that are used to store and organize knowledge by incorporating or chunking multiple elements of information into a single element with a specific function. Schemas can be brought from long-term to working memory to govern activity in the same manner as the epigenetic system can activate or suppress large amounts of genomic information. Whereas working memory might, for example, only deal with one element, a working memory load that can be handled easily, that element may consist of a large number of lower-level, interacting elements organized and stored in long-term memory. Those interacting elements may far exceed working memory capacity if each element must be processed individually. Their incorporation in a schema means that only one element must be processed. If readers of this article are given the problem of reversing the letters of the last word of the last sentence mentally, most will be able to do so. A schema is available for this written word along with lower-level schemas for the individual letters and further schemas for the squiggles that make up the letters. This complex set of interacting elements can be manipulated in working memory because of schemas held in long-term memory.

Skilled performance develops through the building of increasing numbers of ever more complex schemas by combining elements consisting of lower-level schemas into higher-level schemas (i.e., schema construction). If the learning process has occurred over a long period of time, a schema may incorporate a huge amount of information. The automation of those schemas (i.e., schema automation) so that they can be processed unconsciously, further reduces the load on working memory. Because a schema can be treated by working memory as a single element or used unconsciously after automation, the limitations of working memory disappear for more knowledgeable learners when dealing with previously learned information stored in long-term memory. As a result, once information is stored in long-term memory, working memory can handle complex material that exceeds its capacity prior to the information being stored.

Evidence for the critical importance of long-term memory to cognitive functioning comes from the work of de Groot (1965). The only distinction between chess masters and weekend players that he could find was in memory of briefly seen chessboard configurations taken from real games. These results have been replicated in a variety of educationally relevant fields (Chiesi *et al*. 1979; Egan and Schwartz 1979; Jeffries *et al*. 1981; Sweller and Cooper 1985). They indicate the critical importance of long-term memory to cognitive functioning, including problem solving. Expert problem solvers in an area have acquired large numbers of schemas stored in long-term memory. Those schemas allow problem solvers to recognize a problem state and the best moves associated with that state. Based on these results, a major function of instruction is for learners to acquire schemas. These schemas, stored in long-term memory, alter our ability to process information. The ability of working memory to efficiently process large amounts of information previously stored in long-term memory provides a primary rationale for the human cognitive system. We learn in order to be able to carry out tasks that otherwise would be impossible.

Until recently, cognitive load researchers considered working memory as an immutable system with learning facilitated under instructional conditions that keep the load imposed by the learning task within appropriate limits. Research has, therefore, been concerned mainly with developing and researching instructional techniques for managing the load imposed on working memory by complex tasks in individual learning settings (Paas *et al*. 2010). Nevertheless, Geary's (2002, 2007a, b, 2008, 2011; see also, Sweller 2008) evolutionary account of educational psychology, suggests that working memory restrictions may have only a limited importance when acquiring information we have evolved to acquire over many generations. This information is known as biologically primary knowledge. In contrast, working memory restrictions may be critical when acquiring information that is culturally important but that we have not specifically evolved to acquire, known as biologically secondary knowledge.

Biologically primary knowledge is modular in the sense that we may have evolved to acquire some categories of primary knowledge independently and during a different epoch to other categories of knowledge. We have evolved to acquire particular modules or categories of knowledge in order to achieve access to and control of the social, biological, and physical resources that enhance our survival or reproductive prospects. Humans are easily able to acquire huge amounts of biologically primary knowledge outside of educational contexts and without a discernible working memory load. In that sense, biologically primary knowledge does not require the cognitive architecture outlined above.

The manner in which we learn to recognize faces (e.g., Bentin *et al*. 1999) and learn to speak (e.g., Kuhl 2000) provides startling examples of our ability to discover large amounts of complex knowledge without explicit instruction. With regard to speaking, we learn how to simultaneously arrange our lips, tongue, breath, and voice simply by immersion in a listening/speaking society. That learning is unconscious, effortless, rapid, and driven by intrinsic motivation. The concept of a limited capacity, limited duration working memory is irrelevant to the process because we do not have to determine how to process elements of biologically primary information. We *know* which elements to process and how to process them because we have evolved to do so. Not only is hearing, speaking, and face-recognition knowledge acquired at a very young age without explicit teaching, most of us would have little idea how to teach children to speak their native language or to recognize faces.

Biologically secondary knowledge is related to knowledge and expertise that are useful in the social milieu or ecology in which a group is situated. For biologically secondary knowledge that can be found in domains such as reading and mathematics, humans have great difficulty and often need to be extrinsically motivated to acquire relatively small amounts of knowledge. To acquire that knowledge, we usually require explicit instruction in an educational context. Working memory limitations are directly relevant to the acquisition of biologically secondary knowledge because we have not evolved to know how secondary information should be processed. For this reason, cognitive load theory has been applied exclusively to the acquisition of biologically secondary subject matter taught in educational and training contexts. That subject matter, like all biologically secondary information, requires explicit instruction and a conscious effort by learners. In contrast, biologically primary information needs neither explicit instruction nor a conscious effort. Instructional recommendations for biologically secondary information should not be based on the manner in which humans acquire biologically primary information. Nevertheless, given the efficiency of biologically primary systems in the acquisition of knowledge, the question immediately arises whether those primary systems can be used to facilitate the acquisition of secondary knowledge.

Geary's evolutionary educational psychology with its distinction between biologically primary knowledge that we have evolved to acquire, and biologically secondary knowledge that has become culturally important but for many people frequently difficult to acquire, may provide us with a theoretical foundation for designing cognitive load-based instructional design. In this article, we show how the incorporation of this new view of human cognitive architecture into cognitive load theory can provide cognitive load researchers with new perspectives on their findings such as the human movement effect and the collective working memory effect. In addition, an evolutionary educational psychology view can stimulate the consideration of other theoretical frameworks and their associated research findings such as embodied cognition that allows gesturing to reduce cognitive load. In general, we are concerned with the extent to which biologically primary knowledge can be used to facilitate learning in biologically secondary domains.

The Collective Working Memory Effect

From an evolutionary perspective, natural selection promotes the fittest individuals. Although this seems to predispose individuals to selfishness, collaboration can increase the fitness of the collaborators when together they can access more resources than when working individually. A group of collaborating learners can solve complex problems that may be insoluble for an individual learner. Yet for individuals, the best strategy seems to consist in allowing the other learners to devote their cognitive resources to solving the problem and then to gain an advantage from the solution. But, if all learners acted in that manner, any advantage of collaboration would be lost (Heylighen 2000).

The collective working memory effect reflects the finding that collaborating learners can gain from each other's working memory capacity during learning. The effect has been demonstrated in cognitive load research comparing individual to collaborative learning environments. Recently, group or collaborative learning has been recognized as an alternative way of overcoming individual working memory limitations (Kirschner *et al*. 2009a, b, 2011a, b). Collaborative learners can be considered as a single information processing system (Hinsz *et al*. 1997; Tindale and Kameda 2000; Ickes and Gonzalez 1994), consisting of multiple, limited working memories which can create a larger, more effective, collective working space. The result is the collective working memory effect (Kirschner *et al*. 2011a, b; see also, Janssen *et al*. 2010).

According to the current evolutionary perspective of cognitive load theory, humans have evolved to communicate with each other in order to obtain most of their information from each other. The suggestion that humans obtain most of their information from other people led to the borrowing and reorganizing principle (Sweller 2003, 2004; Sweller *et al*. 2011; Sweller and Sweller 2006). This principle states that long-term memory is built primarily by observing and imitating other people, listening to what they say and reading what they write. In other words, humans obtain most of their information by borrowing that information from other people's long-term memory. This process involves constructive reorganization in that new information must be combined with previous information using a constructive process. The principle suggests that information can be better obtained from an instructor, either in person or via instructional materials, rather than discovering information by oneself. Of course, information can just as easily be obtained from other, sufficiently knowledgeable people engaged in the same task during collaborative learning.

Most research demonstrating the borrowing and reorganizing principle is based on individual learning environments using worked examples (e.g., Cooper and Sweller 1987; Paas 1992; Paas and Van Gog 2006; Paas and Van Merriënboer 1994b; Renkl 1997; Sweller 1988; Sweller and Cooper 1985; Tuovinen and Sweller 1999) and animated models (e.g., Wouters *et al*. 2008, 2009, 2010). However, the principle also applies to any information obtained from another human, resulting in collaborative learning environments providing us with an ideal example of the principle at work. Humans collaborate in large part because the people they are collaborating with can provide them with information more efficiently, under many circumstances, than if they had to obtain that information without assistance from others. For a group to carry out a learning task, not all group members need to possess all necessary knowledge, or process all available information alone and at the same time. As long as there is communication and coordination between the group members, the information elements within the task and the associated cognitive load caused by the intrinsic nature of the task can be divided across a larger reservoir of cognitive capacity. Since we have evolved to communicate and coordinate information between each other, general communication and coordination processes are biologically primary.

In terms of cognitive load theory, working in groups, as compared with working individually, has two contrary consequences. First, if biologically secondary information that imposes a heavy cognitive load is distributed over several collaborating individuals, they have to invest less cognitive effort as compared with individuals learning alone. Distributing that working memory load among group members may lead to a large reduction in individual working memory load. Second, while dividing information between individuals reduces cognitive load, that division requires the communication of information and coordination of actions. Communication requires the group members to invest an additional cognitive effort, an effort that individuals do not have to exert.

Communication costs can be divided into two categories. The working memory costs of general communication and coordination processes may be quite low because they are biologically primary. In contrast, the working memory costs of task-specific communication and coordination processes may be substantial, because they are biologically secondary. Therefore, a potential advantage of group learning may only result if the working memory costs are largely biologically primary. The working memory costs of task-specific communication and coordination processes can be decreased by training those processes or by working in carefully structured or scripted learning environments (e.g., Serfaty *et al.* 1998).

In the experiments reported by Kirschner *et al.*, the efficiency of group versus individual learning from tasks imposing a high or low cognitive load was expected to be affected by the trade-off between the advantages of dividing information processing amongst group members and the disadvantages or costs of inter-individual communication and coordination of information. It was hypothesized that learning from tasks imposing a high cognitive load, should lead to more efficient collaborative learning than individual learning. In contrast, when learning from tasks imposing a low cognitive load, individual learning should be more efficient than collaborative learning. In general, the results of Kirschner et al. experiments confirmed this interaction hypothesis. For learning tasks imposing a high load, individual learners did not have sufficient processing capacity to successfully process the information. For collaborative learners, the benefits of distributing the cognitive load among each other proved to be higher than the costs of inter-individual integration and coordination of information. Consequently, learners were able to devote the freed cognitive capacity to activities that fostered learning. For learning tasks imposing a low cognitive load, learners working either individually or collaboratively had sufficient cognitive capacity to process all information by themselves. Hence, inter-individual communication and coordination of information were unnecessary and resulted in transaction costs that were higher than the benefits of distributing the cognitive load across group members during the collaborative learning process. Consequently, when cognitive load was low, qualitative differences in constructed schemas materialized in higher learning efficiency for those who learned individually than for those who learned collaboratively.

The collective working memory effect provides the first example of the potential benefits of using biologically primary knowledge to assist in the acquisition of the biologically secondary information that is the usual subject of instruction. Face-to-face communication with others is a biologically primary task. It is not a task that is characteristically taught in educational contexts. We have evolved to acquire the skills associated with face-to-face communication and so learn these skills easily and automatically simply due to our membership of a society. As a consequence, while communicating is likely to require some working memory resources, particularly for the task-related aspects of the communication process, there may be considerable advantages to being able to communicate when faced with acquiring complex, biologically secondary information.

It should be noted that the cognitive-load-oriented research leading to the collective working memory effect represents only a small part of the immense amount of research conducted in the field of collaborative learning. It is hard to find unequivocal empirical support for the premise that learning is best achieved interactively rather than individually in that research. Empirical evidence comparing collaborative learning with individual learning reveals mixed results. Positive effects are primarily found in highly structured and highly scripted learning environments in which learning processes were bound to strict rules (Dillenbourg 2002). In those environments, students working collaboratively become more actively engaged in the learning process, retain the information being learned for a longer period of time (e.g., Morgan *et al.* 2000), engage in higher-order skills (e.g., Sloffer *et al.* 1999), and engage in activities valuable to the processes of learning such as self-directed learning, negotiating meaning, verbalizing explanations, justifications and reflections, and giving each other mutual support (e.g., Van Boxtel *et al.* 2000).

Along with the positive findings, however, there is also a body of research showing mixed and negative findings regarding both the learning process itself (Gregor and Cuskelly

1994; Heath 1998; Mason 1991) and the dynamics of group formation (Hughes and Hewson 1998; Taha and Caldwell 1993). Groups appear to fall prey to information processing limitations such as underutilizing base-rate information (Tindale 1993), committing additional resources to failing projects (Smith *et al*. 1998), ineffectively sharing information known only by individual group members (Stasser 1999), production blocking (Diehl and Stroebe 1987), and social loafing (Latané *et al*. 1979).

An important characteristic of the cognitive load theory motivated studies on the collective working memory effect is that they were conducted under carefully structured and randomized learning conditions to isolate the cognitive effects of task complexity and minimize the effects of social and motivational factors on collaborative learning. Clearly, the identification of working memory load as a factor determining the effectiveness of collaborative learning represents the modest contribution cognitive load theory can make to the research on collaborative learning. Ultimately, this research requires an interrelated perspective integrating cognitive, social, and motivational aspects of the learning environment but only after all of the individual contributing factors have been studied.

Another important characteristic of the studies on the collective working memory effect is that they were conducted in a traditional face-to-face collaborative learning context. Although we have argued here that we have evolved to acquire the skills associated with face-to-face communication and so applying these skills requires minimal working memory resources, many contemporary learning environments use a computer to mediate the communication between different students or to communicate with students. In computer-mediated communication, the computer can be nothing more than a conduit to another person or object (e.g., teleconferencing) or present virtual social actors that are automated interactants (e.g., social agents). An important question in the context of the evolutionary educational psychology approach pertains to the working memory requirements of such computer-mediated communication and how those requirements can inform the design of computer-mediated collaborative learning environments.

According to Reeves and Nass's (1996) media equation, people tend to treat new technologies as real people and places because the human brain has not evolved quickly enough to assimilate these technologies. One of the important research lines providing evidence for their claim is related to Mayer's (2005) social agency theory, which refers to the idea that social cues in multimedia instructional messages can prime a social response that leads to deeper cognitive processing and better learning outcomes. For example, people learn more deeply when the words in a multimedia presentation are in conversational style rather than formal style (the personalization principle: e.g., Mayer *et al*. 2004; Moreno and Mayer 2004), or when the words in a multimedia message are spoken in a standard accented human voice rather than in a machine voice or foreign-accented human voice (voice principle, e.g., Atkinson *et al*. 2005; Mayer *et al*. 2003). In the present context, social agency theory can be considered as another example of biologically primary knowledge assisting in the acquisition of biologically secondary knowledge. In future research, it would be interesting to investigate whether those social agency effects are also effective for the design of computer-mediated collaborative learning environments.

Human Movement Effect

The human movement effect reflects the finding of neuroscience research that the same cortical circuits that are involved in executing an action oneself, also respond to observing someone else executing the same action. The effect has been used in cognitive load research to investigate learning from dynamic visualizations or animations involving a human movement component. In the current context, we will use the human movement effect as the second example of using biologically primary knowledge to facilitate the acquisition of biologically secondary knowledge.

Cognitive load theorists have argued that dynamic visualizations can be ineffective if they create high extraneous cognitive loads (Ayres and Paas 2007a, b) defined as a cognitive load that can be avoided by changing an instructional design. In this context, an extraneous load can be caused by a number of poor design features. Separating text and a diagram leading to a split-attention effect (e.g., Ayres and Sweller 2005; Chandler and Sweller 1992; Mayer and Moreno 1998), or more endemically, the very transitory nature of dynamic visualizations (e.g., Hegarty 2004; Lewalter 2003), provide examples. By their intrinsic nature, dynamic visualizations change over time, which often involves information disappearing from a screen and so requiring learners to process new information while simultaneously trying to remember and integrate important past information, thus creating an extraneous load as working memory resources are focused on dealing with the demands of the presentation, rather than on learning.

The transient information effect provides a possible explanation why some forms of user-interactivity (for an overview see, Wouters *et al*. 2007), segmentation (for an overview see, Spanjers *et al*. 2010), and attention cueing (for an overview see, De Koning *et al*. 2009) improve the effectiveness of animations. These instructional manipulations reduce transient information and consequently the demands on working memory are reduced. The influence of transient information also explains why in many cases, dynamic visualizations are no more effective than static visualizations. With statics, there is less need to hold information in working memory because in many research designs the sequence of static displays are continuously available without disappearing, and thus can easily be reviewed by the learner.

The transient information argument based on cognitive load theory provides a plausible reason why dynamic visualizations frequently have not produced the desired learning results, particularly when compared with static visualizations. Not surprisingly, there is limited research that has found dynamic visualizations to be more effective than static graphics. Interestingly, under some instructional conditions, such as the use of dynamic visualizations to teach human motor skills, this tension between a limited working memory capacity and transient information seems to be non-existent, with animations being more effective than equivalent static graphics. In particular, the meta-analysis of Höffler and Leutner (2007) showed that superior learning (the largest effect size) was found when the animations were highly realistic and procedural-motor knowledge was involved, such as in learning to (dis)assemble a machine gun. On the surface, the Höffler and Leutner findings are not consistent with the cognitive load theory transient information explanation, as some of the studies used a non-interactive, video-based recording that clearly contained transient information, yet the animation was superior to an equivalent static presentation. To explain this potential contradiction, Van Gog *et al*. (2009) extended the cognitive load theory argument to include a special case for human movement (see also, Ayres *et al*. 2009; Wong *et al*. 2009).

Van Gog *et al*. proposed that the high working memory demand created by transient information in dynamic visualizations is less of a problem if the learning focus is related to human movement, because of the activation of the "mirror-neuron system" (Rizzolatti and Craighero 2004). Observing an action performed by somebody else induces in an observer the tendency to perform an action that is related (Katz 1960). These, often called "ideomotor movements," can occur both when the observer views the execution of the action and when an observer views only the outcome of the action. A theoretical basis for induced action is provided by Prinz's (1997) "common coding principle," which suggests that the perception of an action outcome engages the same neural systems involved in the planning of a future action. This link between perception of action outcome and action execution is supported by physiological studies examining "mirror neurons" in the premotor cortex of monkeys (Gallese *et al*. 1996). Indirect evidence from studies using Transcranial Magnetic Stimulation or brain imaging techniques suggests that the human motor system also has a mirroring capacity and is activated by observing motor actions made by others (for a review see Rizzolatti and 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 process 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 (e.g., Iacoboni *et al*. 1999).

Van Gog *et al*. argued, based on Geary's (2008) biologically primary knowledge concept, that humans have evolved the ability to acquire certain types of knowledge effortlessly. If, as part of this primary knowledge, we have evolved to observe human movement and copy it, then asking learners to observe an animation in order to learn a motor skill may not place an excessive burden on working memory resources. In contrast, learning about biologically secondary knowledge, such as biological or mechanical systems, may require more working memory resources, because humans do not have the same biological (neural networks) advantages.

Two studies recently completed within a cognitive load theory framework provide evidence in favor of the suggestion that learners can gain understanding from observation as well as imitation. In the first study (Wong *et al*. 2009), primary school students were asked to learn origami skills, and in the second (Ayres *et al*. 2009), university students were required to learn to tie knots and complete puzzle rings. Both studies found superior performance when learners observed a dynamic representation rather than a static representation and when they manually had to complete the tasks (observe and imitate). While these studies used tasks associated with human movement, it may be useful for future research to focus on whether it is effective for learning to call upon human movement when teaching non-motor knowledge.

The human movement effect provides the second stream of evidence for the suggestion that the use of evolved, biologically primary knowledge can assist in the acquisition of biologically secondary information. Transient information can substantially increase working memory load when learning from animations. That load can result in the superiority of static graphics. Nevertheless, if the transient, animated information incorporates human movement that we have evolved to learn as a biologically primary skill, animations can be superior to static graphics.

Embodied Cognition

Embodied cognition will be used as the third example of biologically primary knowledge used in the service of acquiring biologically secondary knowledge. The theoretical framework of grounded or embodied cognition is based on the notion that cognitive processes develop from goal-directed interactions between organisms and their environment (Barsalou 1999, 2008; Glenberg 1997; Rueschemeyer *et al*. 2009). Embodied cognition assumes that cognitive processes are grounded in perception and action, rather than being reducible to the manipulation of abstract symbols (Barsalou 1999). Cognitive representations of symbols like numbers and letters are ultimately based on sensorimotor codes within a generalized system that was originally developed to control an organism's motor behavior and perceive the world around it, which has resulted in automaticity of perceptual and motor resonance mechanisms in cognitive tasks. Ample evidence for the embodied cognition framework comes from psychological research in a variety of domains, such as research on action semantics (Lindemann *et al*. 2006), language comprehension (Zwaan and Taylor 2006), and neuroscience (Glenberg *et al*. 2008; Martin 2007). This research shows that visual and motor processes in the brain are active during the performance of cognitive tasks such as reading, comprehension, mental arithmetic, and problem solving, while semantic codes are activated during the performance of motor tasks, suggesting that cognitive and sensorimotor processes are closely intertwined. Gesture and object manipulation are sensorimotor experiences that could be considered as sources of biologically primary information and have been shown to assist in the acquisition of biologically secondary information. Both types of experiences will be described next.

The first type of sensorimotor experience that has been shown to be effective for learning mathematics and science concepts is gesture, either in the case of learners who express information in gesture or learners who observe an instructor expressing information in gesture (e.g., Singer and Goldin-Meadow 2005). Gesture is particularly important in the interaction between learners and teachers, in the sense that learners' gestures communicate to the teacher information about what they know and how they view a problem (e.g., Alibali and Goldin-Meadow 1993; Goldin-Meadow *et al*. 1993) and teachers use gestures when providing instruction to learners (e.g., Flevares and Perry 2001; Roth and Welzel 2001). Learners pay attention to and glean information from the verbal explanations and gestures made by a teacher, and generally understand a message that is divided between gesture and speech better than they understand either speech or gesture alone (e.g., Kelly 2001). Observing gestures made by an instructor can have beneficial effects on children's learning. For example, Perry *et al*. (1995) showed that for 9–11-year-old children learning the mathematical concept of equivalence, instruction that included gestures made by the teacher was more effective than only receiving verbal instruction from the teacher. Similarly, Church *et al*. (2004) showed that children who had received instructional videos about Piagetian conservation tasks with verbal explanations and gestures being made by the instructor outperformed children, who had received the same instructional videos with verbal explanations only.

However, we not only learn more by observing gestures, making gestures can also foster our learning. Broaders *et al*. (2007) showed that when 9-year-old children were instructed to gesture while solving mathematics problems themselves, they learned more from a lesson by the teacher. A study by Cook *et al*. (2008) revealed that instructing children to make particular kinds of gestures while practicing solving mathematics problems themselves after having received explanations by the teacher, advanced their learning compared with children who were instructed only to speak during practice.

These findings support the embodied cognition view that learning by observing an instructor who verbally explains and gestures or by making gestures oneself while giving verbal explanations leads to the construction of higher-quality cognitive schemas than learning by observing or giving verbal explanations without gestures. Higher-quality cognitive schemas are associated with better learning, which materializes in faster and more accurate performance on a learning test. Most importantly, the construction of higher-quality cognitive schemas from verbal explanations with gestures has been shown to be less cognitively demanding than the construction of lower quality cognitive schemas from verbal explanations only. Studies in the domains of mathematics (Goldin-Meadow *et al*.

2001) and Piagetian conservation tasks (Ping and Goldin-Meadow 2010) have shown that the involvement of the more basic motor system in the form of gesturing reduces the working memory load during instruction.

Goldin-Meadow *et al*. (2001) investigated the effects of being allowed to gesture or not gesture in children and adults who had to explain how they solved mathematics problems. As a secondary task they had to remember a list of unrelated words (children) or letters (adults) while explaining how they solved the problem. Performance on the secondary task served as a measure of cognitive load. The higher the load imposed by the primary explanation task, the lower the available cognitive capacity would be for remembering the words or letters of the secondary task (e.g., Brünken *et al*. 2003; Chandler and Sweller 1996; Paas *et al*. 2003; Sweller 1988). As a consequence, the higher the load of the explanation task, the lower the number of items that are likely to be remembered. Goldin-Meadow *et al*. found that children and adults, who were allowed to gesture while explaining how they solved the mathematics problem, experienced a lower cognitive load because they could remember more items than when they were not allowed to gesture.

In a study using Piagetian liquid quantity conservation tasks, Ping and Goldin-Meadow (2010) investigated whether the Goldin-Meadow *et al*. (2001) findings could be explained by the fact that children mostly made gestures that directly pointed out aspects of the mathematics problem, which could free up cognitive resources by serving as a kind of external memory aid, or whether gesturing when speaking about absent objects could make those objects cognitively present, thereby lowering cognitive load. The results revealed that gesturing lowered cognitive load, regardless of whether objects were present or absent. They also found that the cognitive load benefits of gesturing were even higher when the gestures added information to the information conveyed by speech than when the gestures conveyed the same information as speech, while both resulted in a lower cognitive load than not gesturing.

Goldin-Meadow *et al.* have argued that gesture can convey the same basic idea as speech, but it does so using a visuospatial rather than a verbal representational format. This distinct representational format can enrich the way information is coded and might allow gesture to facilitate information processing and reduce effort because of the larger motor movements involved. The associated reduction of working memory load can be argued to free resources that can then be used to construct higher-quality cognitive schemas in long-term memory. An alternative explanation is that gesturing shifts some of the load from verbal working memory to other cognitive systems. This explanation is consistent with results from cognitive neuroscientific research showing that gesture is represented in cortical areas that differ from those that handle verbal materials (e.g., Decety *et al*. 1997). All explanations can be interpreted as examples of biologically primary knowledge associated with gesturing assisting in the acquisition of biologically secondary knowledge.

The second type of sensorimotor experience that is effective in acquiring biologically secondary knowledge is related to the *Moved by Reading* intervention, which was developed by Glenberg *et al*. (2004; see also, Glenberg 2008; Glenberg *et al*. 2007; Marley *et al*. 2007) to improve children's reading comprehension. The intervention consisted of three types of activities designed to teach children how to map words and phrases onto current and remembered experiences. The studies by Glenberg *et al.* typically asked children to read texts, for example about activities within a farm scenario, and at the same time, provided them with access to a set of toys, such as a barn, a tractor, and different animals. A green traffic light was used during critical sentences as a cue for the children to act out a sentence with the toys (e.g., "The farmer brings hay to the horse"), either physically, by imagining, or by computer-assisted manipulation of the toys, thereby connecting words to particular objects and syntactic relations to concrete bodily experiences (Glenberg *et al*. 2011). In the "imagine" manipulating conditions, the children were taught to imagine how they would interact with the toys to act out a sentence after they had physically manipulated the toys. In the computer manipulation condition, children had to manipulate images on the computer screen using a mouse. The manipulation conditions were compared regarding their performance on a comprehension test to a control condition in which the children, instead of manipulating the toys, had to re-read the critical sentences. The results of the different studies revealed substantially better comprehension performance in the manipulation conditions than in the control conditions.

The results regarding the computer manipulation condition, which were similar to those of the physical and imagine manipulation conditions, suggest that effective embodied representations do not require activity with real objects. This observation is consistent with the findings of studies into the human movement effect, which indicate that representing the hands is not necessary for learners to construct effective embodied representations from dynamic visualizations representing a typical manual skill, such as origami (Wong *et al*. 2009). In addition, the results of Ping and Goldin-Meadow (2010) show that gesturing lowered cognitive load and resulted in better recall performance than non-gesturing, regardless of whether objects were present or absent.

It is interesting to note that with regard to object manipulation, children need to manipulate objects to understand written text that they may be perfectly capable of understanding if the same information is presented in spoken form. Reading is a biologically secondary activity while listening is biologically primary so the cognitive load associated with decoding written text may be relevant. Decoding biologically primary spoken text may impose a minimal cognitive load compared with decoding biologically secondary written text and so the assistance of object manipulation may be unnecessary when dealing with spoken text. Using biologically primary information to assist in the acquisition of other biologically primary information, may yield few benefits compared with the use of biologically primary information to assist in the acquisition of biologically secondary information. Future research, should repeat the experiments of Glenberg *et al.* with spoken rather than written text.

Unlike the research on gesturing, research on using the manipulation of objects to improve reading comprehension has yet to determine if object manipulation reduces working memory load during instruction. Future work is needed to determine if load reduction materializes with object manipulation in the same way as with gesturing.

Biologically primary information is modular with most primary skills probably evolving independently of each other and indeed, probably at different evolutionary epochs. We may have evolved the use of gestures before the use of speech and almost certainly evolved the use of object manipulation prior to speech. Both gesturing and object manipulation may be very old, very well-developed skills that are acquired easily and can be used with a minimal working memory load. One of their functions may be to reduce working memory load when dealing with biologically secondary knowledge such as learning mathematics and reading comprehension. The work of Goldin-Meadow *et al.* and Glenberg *et al.* strongly supports this suggestion.

Discussion and Conclusions

The major purpose of this paper has been to indicate that biologically primary knowledge that makes minimal demands on working memory resources can be used to assist in the acquisition of the biologically secondary knowledge that provides the content of most instruction and that imposes a high working memory load. Evidence for this suggestion can be found in the collective working memory effect, the human movement effect and in embodied cognition through the use of gestures and object manipulation. The collective working memory effect indicates that our primary skill in communicating with others can be used to reduce individual cognitive load when acquiring secondary knowledge. The human movement effect demonstrates that we are able to overcome transience and the resultant cognitive load of animations if those animations deal with human motor movement because we may have evolved to readily acquire motor movement knowledge as a primary skill. The use of gestures and object manipulation are primary skills that do not need to be explicitly taught but can be used to acquire the secondary skills associated with instructional content.

Another recent demonstration of how human movement as a primary skill can be used in the acquisition of secondary skills comes from a study of Shoval (2011) on the use of "mindful movement" in cooperative learning about angles in geometry class. Mindful movement is defined as the use of body movements, for instance children forming a circle, for the purpose of learning about the properties of a circle. The use of mindful movement was expected to be particularly effective for children who are able to cooperate but are not yet capable of high-level verbal interaction. Shoval found that, compared with the conventionally taught control group, the experimental group using mindful movement in cooperative learning obtained better results.

There are other, older cognitive load effects that may similarly rely on biologically primary knowledge assisting the acquisition of biologically secondary knowledge. For example, the modality effect occurs when learners presented related information in audiovisual form with spoken text learn more than when the information is presented in a visual only form with written text (Mousavi *et al.* 1995; Tindall-Ford *et al.* 1997). The effect has been explained within a cognitive load theory context by suggesting that effective working memory capacity is increased by using both auditory and visual processors. That increase may be due to biologically primary knowledge. We may have evolved to listen to someone discussing an object while looking at it. We certainly have not evolved to read about an object while looking at it because reading itself requires biologically secondary knowledge.

Of course, listening to someone involves transitory information because spoken information is generally transitory. Spoken information must be sufficiently low in content and complexity (element interactivity) to enable it to be processed and held in working memory. The advantage of using the biologically primary knowledge associated with listening and looking simultaneously may disappear when dealing with lengthy, complex, spoken text. Under those circumstances, the modality effect may disappear or even reverse, with written text being superior to spoken text (Leahy and Sweller 2011).

These independent research areas are all linked by the suggestion that biologically primary knowledge can be used to assist in the acquisition of biologically secondary knowledge. One of the considerations associated with this general hypothesis concerns the extent to which we can distinguish between biologically primary and secondary knowledge. The concepts are well defined. We have evolved to acquire biologically primary knowledge in modular form. We are able to acquire biologically secondary knowledge and may need to for cultural reasons but we have not specifically evolved to acquire that knowledge. Despite the concepts being well defined, it may not always be obvious in the absence of an evolutionary history into which category a particular skill should be placed. At present, the clearest marker is whether most members of a population will acquire the skill without tuition. In the case of gestures and oral communication in a social context, we do not have to explicitly teach the required skills—they are unlikely to appear in any syllabus documents. Human movement on the other hand, is explicitly taught. Our suggestion that it is a biologically primary skill comes from other sources—neurological studies on the mirror-neuron system. It also should be noted that many skills may consist of a combination of primary and secondary knowledge and so we may be dealing more with a continuum than a dichotomy. Where a skill is placed on that continuum may depend on the relative ratios of primary and secondary knowledge required.

We suggest that the distinction between biologically primary and secondary knowledge is important for research in educational psychology. It is possible that some of the skills currently the subject of extensive research programs consist largely of biologically primary knowledge. Very general skills provide an example. We are likely to have evolved general skills such as, for example, general problem solving. As far as we are aware, there are no data demonstrating that a general problem solving strategy such as means-ends analysis (Newell and Simon 1972) is teachable. A means-ends strategy requires us to search for problem solving operators that will reduce differences between a current problem state and a goal state. If means-ends analysis is a biologically primary skill and we have evolved to use the strategy without explicit tuition, attempting to teach it is likely to be ineffective.

We suspect the same can be said for most general cognitive and metacognitive strategies. We may automatically acquire them at a very young age because they are biologically primary skills essential for human survival. Frequently, the precise skills are not specified in empirical work and so it is not clear whether any documented improvements are due to the acquisition of an unspecified general skill or due to an improvement in biologically secondary, domain-specific knowledge. It is essential that studies claiming to demonstrate the effectiveness of teaching very general skills include far transfer tests to indicate that improvements in performance are not just due to increases in domain-specific knowledge. If very general, biologically secondary cognitive or metacognitive skills exist, they need to be clearly specified and the extent to which they are teachable demonstrated using far transfer tests. Such biologically secondary skills may not exist if we have evolved to acquire important, general skills. We need to at least consider the possibility that all very general skills are biologically primary and so cannot be taught.

It needs to be emphasized that while we have suggested that biologically primary skills cannot be explicitly taught because we have evolved to acquire the relevant skills automatically, it does not follow that the skills are not learned, nor does it follow that we do not take actions to ensure they are learned. Our argument is that the actions we take to ensure that biologically primary skills are learned are themselves biologically primary. We take such actions automatically and unconsciously because we have evolved to take such actions. Csibra and Gergely (2009), in discussing "natural pedagogy" provide some examples of such processes. For example, learning how to open a milk carton is a biologically secondary skill that we have not specifically evolved to acquire. In contrast, showing someone how to manipulate an object to reach a goal such as opening a milk carton may be biologically primary. The act of demonstrating physical manipulation is a complex act but we do not need to make it part of any formal curriculum because we engage in that natural pedagogy automatically.

Similarly, when shown how to open a milk carton once, we will generalize that knowledge to all situations that we perceive to be similar. Again, such "one-trial-learning" is biologically primary. We do not need to teach people to generalize because it is a biologically primary skill. We may need to teach people to open milk cartons because that knowledge is biologically secondary. Acquiring that secondary knowledge relies heavily on primary knowledge. The natural pedagogy examples discussed by Csibra and Gergely (2009) may provide an example of the use of biologically primary knowledge that does not need to be explicitly taught, in the service of acquiring biologically secondary knowledge that does need to be explicitly taught. As Csibra and Gergely speculate "…communication of generic knowledge was selected for during hominin evolution…" (p. 148). Biologically primary knowledge is defined in precisely this manner. The communication of generic information may be too important to be anything other than biologically primary.

While general skills may be primary in nature and so essentially unteachable because they are acquired automatically, it does not follow that they are instructionally unimportant. Their major function may be reflected in the use of biologically primary knowledge discussed in this paper. It may be possible to galvanize general, primary skills to facilitate the acquisition of the secondary skills that are characteristically the subject matter of cognitive load theory based research and that are taught in instructional contexts. Previously acquired general skills, biologically primary in nature, may be of assistance when acquiring biologically secondary skills. Organizing general skills to assist in the acquisition of subject matter knowledge may be more productive than attempting to teach skills that we have evolved to acquire automatically.

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