The Roles of Working Memory and Cognitive Load in Geoscience Learning

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ABSTRACT

Working memory is a cognitive system that allows for the simultaneous storage and processing of active information. While working memory has been implicated as an important element for success in many science, technology, engineering, and mathematics (STEM) fields, its specific role in geoscience learning is not fully understood. The major goal of this article is to examine the potential role that working memory plays in successful geoscience learning. We start by reviewing two popular approaches to studying working memory in science learning—the individual differences approach and the cognitive load approach—and consider how these two approaches have been utilized in geosciences education research. Next, we highlight examples of various activities and curricular materials that have been used in geoscience classrooms in an effort to improve student learning and offload working memory resources, including using concept sketches and providing varying levels of scaffolding. We outline recommendations about how to structure geoscience classrooms and labs to maximize student learning and suggest potential avenues for future research aimed at investigating the role of working memory in geoscience learning. © *2017 National Association of Geoscience Teachers*. [DOI: 10.5408/16-209.1]

Key words: working memory, cognitive load, geoscience education

INTRODUCTION

Learning in geoscience classrooms is an intensely cognitive process, as students try to make sense of an inherently complex three-dimensional (3D) world that has changed dramatically over time. In the learning process, students interact with diverse sensory inputs that can be auditory (lectures, narration, or discussion), visual (textbooks, presentation slides, or maps), or even kinesthetic (scratching a mineral or measuring structural attitudes in an outcrop). For learning new concepts and content in the geosciences, as in all domains, the new information must be held temporarily, processed, and then saved in memory for later. Each of these three steps must be successful for learning to occur. The first involves simple storage of information for seconds to minutes in what is often called short-term memory. The third step involves long-term memory, from which information can be retrieved hours, days, or years later for further mental reprocessing. This article is about the middle step—the simultaneous holding and processing of information, a concept referred to as working memory by cognitive scientists. Measures of working memory capacity correlate positively with many aspects of cognition, including spatial visualization, fluid intelligence, and reading comprehension (Daneman and Carpenter, 1980; Kyllonen and Christal, 1990; Lohman, 1996; Engle et al., 1999). An understanding of working memory, and of a related concept called cognitive load, is critical in designing and implementing courses to provide students with the best opportunity to learn. An understanding of these concepts has helped guide work designing courses and learning materials in many domains, including mathematics, physics, and chemistry (e.g., Johnstone et al., 1993; Taber, 2013; Toll and Van Luit, 2013). Here, we review the concepts of working memory and cognitive load and summarize the results of cognitive and science education research on how these issues affect student learning in an effort to develop capacity for analogous work within the geoscience community. To that end, we also provide examples and recommendations about how to structure geoscience classrooms and labs to consider the impact of working memory and cognitive load and maximize student learning.

Because working memory is a critical element of complex cognition, it is heavily involved in learning science, as well as learning in general. Working memory has been implicated as an important element for success in many areas of science, technology, engineering, and mathematics (STEM) (Gathercole et al., 2004; Passolunghi et al., 2007; Alloway and Alloway, 2010; Alloway and Passolunghi, 2011). While some areas of STEM education have a substantial literature indicating a role for working memory, the specific role of working memory in geoscience learning has not been fully elucidated. Thus, the goal of this paper is to examine prior research on working memory and cognitive load in STEM education more broadly and apply those findings to consider the potential role that working memory plays in successful geoscience learning. Specifically, a contrast will be made between studies that consider working memory capacity as an individual difference variable and those that measure and manipulate cognitive load. Studies that consider working memory as an individual differences variable focus on how people with varying levels of working memory capacity perform on learning tasks, whereas studies on cognitive load focus on how learning materials or instructional methods can overwhelm students and impede their learning (without directly measuring working memory capacity in individual students). Examining this contrast will

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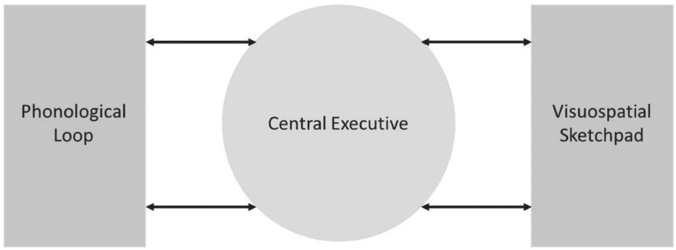


FIGURE 1: Baddeley and Hitch's (1974) early model of the working memory system.

help to clarify for the geoscience education community what cognitive load is and is not and explain why this distinction is important for research on the role of working memory in geoscience learning.

An additional goal is to provide a process-based account of the potential role for working memory in domain-specific geosciences learning and problem-solving tasks—in particular, to elucidate what aspects of working memory may contribute to comprehending complex 3D spatial relations and visualizing geological transformations. From one perspective, individual differences in working memory capacity may contribute to geoscience learning by allowing some students to actively maintain and manipulate larger amounts of information than others. Alternatively, individual differences in working memory capacity may contribute to more effective integration and mental model building by allowing some students to direct their focus to more relevant parts of a problem and perhaps help them to develop novel ways of completing a task. We provide suggestions for future research and specific teaching and learning strategies for geoscience instructors. The benefit of investigating the interactions between students' individual differences in working memory capacity and specific learning and teaching strategies will be discussed in greater detail. Furthermore, an argument will be made for the necessity of considering individual differences in working memory capacity when conducting research on developing cognitive supports in education.

WHAT IS WORKING MEMORY?

Everyday tasks, such as reading the newspaper, figuring out how to split the bill at a restaurant, and putting together new furniture, all involve multiple steps that need to be kept track of in order to complete the task at hand. Working memory is the construct that has been used in cognitive psychology to refer to the mental system that is responsible for maintaining all of the task-relevant information while performing a task (Miyake and Shah, 1999). More specifically, working memory is defined as a system that enables the temporary storage of a limited amount of information and keeps that information available for access by other cognitive processes—it is a cognitive system that allows simultaneous storage and processing of active information.

The concept of a limited-capacity working memory system that is separate from a short-term memory system was originally developed by Baddeley and Hitch (1974). They suggested that the working memory system has three major components: a phonological loop, a visuospatial sketchpad, and a central executive (Fig. 1). The phonological loop was argued to be responsible for holding and manipulating speech-based information, whereas the visuospatial sketchpad was responsible for holding and manipulating visual and spatial information. In this context, *visual* refers to observable characteristics of an object, such as its color or shape, whereas *spatial* refers to the object's location, orientation, and setting relative to other objects. The central executive was considered to be a supervisory system that is responsible for attentional control and for regulating the flow of information stored within the two subsystems when performing cognitively demanding tasks.

This multicomponent model has been the subject of a great deal of research, which has helped to strengthen support for the model and to refine and further specify its structure and function. In a later version of the model, Baddeley (2000) proposed an additional temporary storage system called the episodic buffer, which is assumed to serve as an interface between the two subsystems and the long-term memory. This more recent model also proposed that each subsystem involves two subcomponents, one component for storing active information and another for rehearsing or refreshing active information. Specifically, within the phonological loop, when verbal information is encoded, it is passively stored in the phonological store and then an articulatory rehearsal mechanism is used to recite the information in the store in order to prevent rapid decay. Some evidence to support the existence of the rehearsal system within the phonological loop is provided by investigations into the word-length effect (Baddeley et al., 1975), in which recall was better for shorter words than for longer words. The prevailing explanation for this is that verbal rehearsal takes longer for long words than for short words and therefore longer words are more susceptible to decay.

While the structure of the visuospatial sketchpad is less understood than the phonological loop, similar subcomponents have been proposed. It has been suggested that within the visuospatial sketchpad system, perceptual information accesses knowledge previously stored in long-term memory and abstract representations of this knowledge are fed into a passive visual store and rehearsed in an active spatial store (Logie, 1995, 2003). Rather than an inner voice like that presumed to be occurring in the phonological loop, Logie (1995) describes an "inner scribe" that is responsible for carrying out rehearsal. There is also some evidence to suggest that the visuospatial sketchpad may be further subdivided into one component specialized to deal with visual information (e.g., texture) and another for spatial information (e.g., relative object location) (Vicari et al., 2006). The distinction between a subsystem for maintaining visual object representations and another for spatial representations is in line with observations about the visual system. Specifically, neuroscience research has shown that there are distinct neural pathways involved in processing visual features versus spatial properties of objects (Mishkin and Ungerleider, 1982). Several studies have shown that spatial working memory also is separate from verbal working memory (Shah and Miyake, 1996; Hegarty et al., 2000) and that different spatial tasks may require varying levels of spatial working memory (Miyake et al., 2001). While there is considerable debate in the working memory literature about the exact structure of the system (see Conway and Jarrold, 2008, for a review of approaches to working memory models), the idea that working memory allows individuals to simultaneously store and process information in order to achieve complex task relevant goals is well established.

HOW IS WORKING MEMORY CAPACITY MEASURED?

Psychologists have long been interested in the accurate measurement of individual differences in memory. Early intelligence tasks included measures of short-term memory span (simple span). In these tasks, participants are given a list of to-be-remembered items, including letters, digits, words, or shapes, and then immediately after presentation of the last item are asked to recall the list in the correct serial order (Unsworth and Engle, 2007). For example, in a simple letter-span task, participants may see the letters P, S, L, T, and Q and then would be asked to recite these back in the same order. Any deviation from the original presentation would count as an error, and the lengths of to-be-remembered lists typically vary from two to seven items.

However, the hallmark of working memory is that it represents not just storage but also simultaneous processing. Therefore, measures of working memory capacity, commonly referred to as complex-span tasks, require the participant to also engage in some kind of processing task that is unrelated to the storage task. For example, similar to simple-span tasks, participants must recall a set of items in correct serial order, but interleaved between the presentations of each to-be-remembered item is a processing task. The processing tasks can vary but typically include reading a sentence, solving an arithmetic problem, or making a symmetry judgment. For example, in the operation-span task, participants solve a simple math problem, are presented a letter, solve another math problem, and finally are presented another letter; this procedure can continue anywhere from two to seven times. At the end of the trial, they are asked to recall all of the letters they saw in the correct serial order. Such complex-span tasks are interpreted to measure working memory capacity, whereas simple-span tasks measure short-term memory capacity. Previous work has demonstrated that these two constructs are separable and that complex-span tasks are better than simple-span tasks at predicting higher-order cognitive abilities, such as verbal aptitude (e.g., the verbal subtest of the Scholastic Aptitude Test), quantitative aptitude (e.g., the quantitative subtest of the Scholastic Aptitude Test), and general fluid intelligence (e.g., analogical thinking tasks and visual-series-completion tasks, such as Raven's Advanced Progressive Matrices) (Daneman and Carpenter, 1980; Dixon et al., 1988; Cantor et al., 1991; Conway and Engle, 1996; Daneman and Merikle, 1996; Engle et al., 1999; Kail and Hall, 2001; Conway et al., 2002).

AN INDIVIDUAL DIFFERENCES APPROACH TO UNDERSTANDING WORKING MEMORY CAPACITY AND STEM LEARNING

One approach to examining the role of working memory in learning has been to look at individual differences in working memory capacity. In this line of research, working memory capacity is thought of as a trait of the individual learner and represents that learner's central executive or ability to control one's attention. This approach to studying working memory originated from a seminal study by Daneman and Carpenter (1980). The goal of their study was to assess the possible role of working memory capacity in language comprehension. In this research, participants were required to read a series of sentences and then subsequently recall the last word of each sentence. Performance on this task was able to predict performance on three separate measures of reading comprehension. Measures of working memory capacity have also been shown to predict other aspects of text comprehension, including prose composition (Benton et al., 1984), learning from complex instructions (Engle et al., 1991), and logic learning (Kyllonen and Stephens, 1990).

More recently this approach has been applied to STEM learning. One area that has received a lot of attention is in mathematics. A substantial literature demonstrates that working memory capacity is related to numerical and mathematical abilities used for counting, which is a necessary step when trying to solve simple addition and subtraction problems or more complex arithmetic problems (Adams and Hitch, 1997; Bull and Scerif, 2001; Alloway et al., 2005; Anderson, 2007; Holmes et al., 2008; De Smedt et al., 2009; Lee et al., 2009; Alloway and Alloway, 2010; Alloway and Passolunghi, 2011). One study demonstrated that working memory capacity was a significant predictor of mathematics learning at the beginning of primary school, whereas short-term memory and phonological ability were not (Passolunghi et al., 2007). In line with this finding, limitations in working memory have been identified as one of the key factors associated with general learning disabilities (Alloway et al., 2009; Tillman et al., 2011) and with mathematical learning disabilities (Pickering and Gathercole, 2004; Swanson and Jerman, 2006; Geary et al., 2012).

Science domains have received less attention in terms of understanding the role of individual differences in working memory capacity in learning, but several studies have revealed a positive correlation between science achievement and working memory capacity. For example, Gathercole et al. (2004) assessed working memory capacity of students through a series of dual tasks involving forward and backward digit- or letter-span tasks and reading tasks. They found that achievement in science, as indicated by performance on a standardized school assessment, was strongly correlated with working memory capacity and that test scores significantly differed between groups with high and low working memory capacity.

The role of individual differences in specific STEM domains has also been investigated. For instance, individuals with high working memory capacity performed better than those with low and intermediate working memory capacity, based on a physics test that assessed understanding of refraction and lenses, heat, buoyancy, and Ohm's law (Chen and Whitehead, 2009). Similar results in chemistry showed that students with high working memory capacity performed better on a chemistry test assessing understanding of moles than those with intermediate or low working memory capacity (Danili and Reid, 2004). Performance of the chemistry students was increased by using instructional materials designed to minimize the impact of working memory capacity limitations, such as by presenting the materials in a stepwise fashion rather than all at once, by more carefully introducing diagrams and models to reduce noise, and by adding dialogue boxes in strategic locations to focus student attention on the most important concepts. In biology, working memory capacity has also been shown to predict conceptual learning about DNA (Rhodes et al., 2014) and plant taxonomy (Banas and Sanchez, 2012).

Some work has also been conducted in the area of geosciences learning. In a study by Sanchez and Wiley (2006), participants read an expository text about the cause of ice ages in three situations: text that was not illustrated, illustrated with conceptual diagrams, or illustrated with nonconceptually relevant images. Participants completed operation and reading span tasks and wrote an essay explaining the causes of ice ages based on what they read in the text. Results indicated that individuals with low working memory capacity performed worst when the text was paired with nonrelevant images, whereas individuals with high working memory capacity were not affected by the presence of these irrelevant pieces of information. A follow-up experiment with eye tracking replicated this finding and demonstrated that the individuals with low working memory capacity were attending to the irrelevant images at inappropriate times, such as midsentence, effectively disrupting their comprehension of the text and harming the integration and mental model building process. Similar eye tracking studies, using textbook-style geoscience materials, have documented that students switch their attention from text to figures at times different from when those figures are referenced in the text (Busch et al., 2010a, 2010b). Sanchez and Wiley (2014) also demonstrated that working memory capacity was a significant predictor of learning from an expository text on volcanoes and plate tectonics.

Altogether, these results indicate an important role for working memory in successful STEM learning. In STEM, students need to be able to understand complex processes with many interrelated concepts and causal connections. Therefore, while being able to store a large amount of information may be helpful, what is more important is being able to actively work with and integrate that information into an accurate mental model. While the previously discussed results do not directly test this notion, they do lend support for the idea that working memory is important because it allows students to more effectively select, coordinate, and integrate relevant information into a single representation.

A COGNITIVE LOAD APPROACH TO UNDERSTANDING WORKING MEMORY AND STEM LEARNING

Another approach to understanding the role of working memory in STEM learning has been to focus on decreasing the information load, or cognitive load, in the learning materials. This approach comes out of Sweller's (1994) cognitive load theory, which suggests that working memory capacity imposes a limit to the amount of information a person can process in any given cognitive activity. This theory posits that if the cognitive load of a learning task exceeds the limit of one's working memory capacity, then learning will be diminished. Cognitive load theory originated from research on mathematical problem solving, which found that students were able to learn more effectively from worked examples than from less-structured, conventional problem-solving scenarios (Sweller, 1988). Sweller suggested that the act of problem solving, coupled with the need to learn from those acts or to abstract the underlying principles, required too many resources and therefore hindered learning. Put more generally, students have a limited amount of resources for coordinating and integrating new and complex information; therefore, materials that provide more structure allow limited resources to be allocated to integration and mental model building rather than interpreting the materials themselves.

Two major factors are argued to contribute to the amount of cognitive load—extraneous cognitive load, which is caused by inappropriate instructional design, and internal cognitive load, which refers to the natural complexity of the information being processed (Low and Sweller, 2005). Altogether, research out of this tradition assumes that poor learning outcomes are due to learners being put under load by the materials they are given, such that the amount of information being given to them, or the way in which it is given, is overwhelming the capacity of learner's working memory system. What is most important to point out about this literature is that the research has focused on the learning materials or instructional methods themselves, not on the individual characteristics of the learners.

While the question of how to most accurately and reliably measure cognitive load is still debated, a review by Sweller et al. (2011) indicated four primary measures—indirect, subjective, secondary task, and physiological measures. Indirect measures include performance or error profiles between problems. For example, one might find that error rates increase when problem solving requires more sophisticated decision-making or when multiple variables need to be considered. This increased error rate is taken as an indirect indicator of increased cognitive load on these items (Ayers, 2006). Subjective measures are the most commonly used method for measuring cognitive load. Typically, these subjective rating scales ask participants to report the perceived difficulty of a task or how much mental effort they invested while completing a task (Paas et al., 1994). Secondary task measures, sometimes referred to as dual task methods, are also frequently used. In these methods, participants must complete a secondary task while simultaneously completing a target task. If decreased performance is observed on some items during the target task, it is presumed that those items are cognitive resource intensive and therefore impose a heavy cognitive load compared to items for which performance decrement is not observed (Sweller et al., 2011). The fourth category of cognitive load measures is physiological measures, which include heart rate (Paas and van Merriënboer, 1994) or brain activity (Antonenko and Niederhauser, 2010).

More recently, eye movement and changes in pupil size have been shown to indicate changes in cognitive load (van Gog and Jarodzka, 2013; Mitra et al., 2016). What is most important to point out about these various methods for measuring cognitive load is that they reflect features of the tasks that participants are completing. More specifically, one might expect that the levels of these measures would change from task to task depending on how difficult or complex the tasks are. However, measures of working memory capacity reflect characteristics of the participants themselves and should remain relatively stable, regardless of the task at hand.

COGNITIVE LOAD THEORY AND MULTIMEDIA LEARNING IN STEM

Most research on cognitive load theory and science learning has come out of the multimedia learning literature (Mayer, 2005). The main case for multimedia instruction is that it more accurately aligns with the way the human mind works. Specifically, Mayer's theory of multimedia learning suggests that humans have two systems for processing information: one for verbal materials and another for visual materials. If materials are presented through both channels of information processing rather than only one, it takes advantage of the full capacity of humans for processing information. Another important component of Mayer's theory of multimedia learning is that in order for learning to occur, one must actively engage in cognitive processing to construct a coherent mental representation. Therefore, just being able to store both visual and verbal information is not enough for learning to occur; one must also coordinate and integrate the information in each system to make sense of it all and build a mental model.

While presenting a combination of text and graphics as a means for not overloading the working memory system seems intuitive, not all presentations have led to better learning results. The theory of multimedia learning suggests that when designing learning materials, the presented material should have a coherent structure and be presented in a manner that provides the learner with guidance as to how to build an accurate mental model. In particular, Mayer (2005) lays out several principles of multimedia instructional design that are aimed at minimizing the effects of extraneous processing. The coherence principle asserts that eliminating extraneous material that is not directly relevant to understanding the main concepts is important because it reduces the amount of information that must be initially processed and allows for limited cognitive resources needed for integration and coordination of information to be allocated more effectively. For example, better conceptual comprehension occurred by removing interesting facts from expository text about lightning formation (Harp and Mayer, 1997, 1998), removing entertaining but irrelevant auditory materials from instructional videos on lightning formation and hydraulic brake systems (Moreno and Mayer, 2000), and removing unnecessary quantitative information such as equations and symbols (Mayer and Jackson, 2005). Similarly, the redundancy principle asserts that people learn better when repeated or redundant information is removed (Mayer et al., 2001). For example, redundancy occurs when both narration and onscreen text are used to present the same information but is avoided when narration accompanies slides without text. This style of presentation provides the learners with guidance as to how the information should be coordinated in order to build a coherent structure. The signaling principle asserts that highlighting essential material by adding overview sentences, headings, or specific narration that emphasizes main ideas will guide the learner's attention and minimize processing of extraneous material. The effectiveness of signaling on learning has been shown in lessons on how airplanes achieve lift (Mautone and Mayer, 2001), the structure of polysaccharide molecules (Stull and Mayer, 2007), lightning formation (Harp and Mayer, 1998), and detecting geological features in landscape photographs (Coyan et al., 2010a, 2010b). Finally, the spatial and temporal contiguity principles assert that people learn better from multimedia presentations when corresponding words and pictures are presented near each other on the page or screen (spatially contiguous) and when corresponding narration and animation are presented simultaneously rather than successively (temporally contiguous) (Ginns, 2006).

What all of these principles have in common is that they not only demonstrate attempts to reduce the amount of information being presented to the student but also demonstrate methods for providing the learner with guidance for how to structure a mental model. Just as Sweller's (1988) initial work on worked examples provided students with structure for completing problem solving and abstracting the underlying principles, Mayer's principles of multimedia design are meant to provide guidance and allow resources to be allocated to the important learning process of mental model building.

Cognitive load and multimedia design principles have been explored across a variety of STEM domains, including mathematics (Tarmizi and Sweller, 1988; Mayer and Anderson, 1991, 1992; Mousavi et al., 1995; Atkinson, 2005), chemistry (Carlson et al., 2003; Kozma and Russell, 2005; Lee et al., 2006), biology (Chandler and Sweller, 1991; Moreno, 2004), meteorology (Mayer et al., 2001; Lowe, 2005), and physics and engineering (Kalyuga et al., 1998; Renkl et al., 2002). Little research has looked specifically at manipulating the cognitive load of materials and instructional methods in geology, although some educational materials have been designed to explicitly address the multimedia effect and reduce cognitive load (Reynolds and Johnson, 2015, pp. XV–XIX). In one study of geology learning, adding pictures for learning to a computer-based geology simulation improved learning beyond that of a no-pictures group and of a group that received both pictorial and verbal prompts (Mayer et al., 2002). The improvement in learning could be because the pictures reduced extraneous processing and reduced the complexity of the task.

Despite the lack of research specifically investigating the role working memory and cognitive load in geosciences learning, it is particularly important to pursue, because many of the most important concepts in geoscience are too large to for a person see and happen too slowly for a person to experience. Thus, learning these concepts requires individuals to develop complex yet accurate internal mental representations, which they must rely on when making inferences or solving problems. Information from textbooks and information from field experiences need to be integrated with each other but also need to be integrated into existing mental models. Therefore, simply finding ways to reduce the amount of information a student is exposed to is unlikely to improve learning or problem solving. Rather, supporting learning for a range of students requires developing methods for improving the management and integration of this information with long-term memory representations.

WHAT THESE METHODS TELL US ABOUT WORKING MEMORY CAPACITY AND STEM LEARNING

Altogether, research from the two perspectives—the individual differences perspective and the cognitive load perspective—offer different yet complimentary information about the role of working memory in STEM learning. Overall, both of these lines of research indicate that working memory is important in science learning, partly because most science topics require the integration and maintenance of multiple pieces of information presented across multiple representations and modalities. In addition, these lines of research suggest that the way topics are taught and the way learning materials are presented needs to be carefully considered. The individual differences work indicates that learning in STEM is predicted by working memory capacity, while the research on cognitive load indicates that certain styles of instruction and presentation can be helpful or detrimental to learning. Unfortunately, little work has combined these two approaches to more directly assess the interaction between individual differences in working memory capacity and instructional manipulations meant to decrease extraneous load, and even less work has attempted to identify the specific processes in learning and problem solving that are especially dependent on the working memory system.

Geology is one of the most visual sciences, relying heavily on visualizations and multimedia presentations for learning (Reynolds et al., 2005, 2006; Kastens and Ishikawa, 2006), often requiring students to continuously integrate textual and visual information. It is important, therefore, that geoscience education researchers begin to consider the potential role for working memory in domain-specific geosciences learning and problem-solving tasks. In particular, we need to understand what aspects of working memory may contribute to comprehending complex 3D spatial relations and visualizing geological transformations, how working memory affects learning from multimedia geology lessons, and which students may be particularly at risk for struggling to learn in geology. The question is not simply about whether or not working memory matters for learning in geosciences but about how, when, and for whom it matters. While the work coming out of the individual differences literature tells us that working memory is important for learning, it does not provide information about which processes are most reliant upon working memory resources or provide guidance for how to support the learning of low-capacity or at-risk students. Similarly, work coming out the cognitive load literature tells us what design principles seem to improve learning overall, but it does not measure individuals' working memory capacity and cannot tell us whether these manipulations decrease cognitive processing requirements and whether they are especially effective for low-capacity individuals. More specifically, by incorporating the individual differences approach and the cognitive load approach into a single research design, it would be possible to understand if and what kind of instructional or material changes help individuals with low working memory capacity and whether these changes interfere with the learning of individuals with middle to high working memory capacity or, vice versa, changes that appear to broadly reduce working memory load only benefit individuals with middle to high capacity. If changing instruction or learning materials only helps individuals with high working memory capacity, then separate forms of instruction may need to be developed for specific subsets of students.

CONSIDERING A PROCESS-BASED ACCOUNT OF WORKING MEMORY IN GEOSCIENCES

While it is useful to know that working memory capacity predicts learning across all STEM domains and that certain materials can overload this capacity, it is more useful to begin to understand how and why this is the case. Considerable evidence has appeared over the last 15 years concerning the role of working memory in mathematical cognition and may provide a useful example for the geoscience cognition community. LeFevre et al. (2005) argue that the literature supports a clear generalization concerning the positive relationship between the complexity of math problems and the demand on working memory for problem solving. They suggest that one aspect of this relationship involves manipulating numerical values, such that working memory becomes increasingly involved as the numbers in the problems grow larger (the problem-size effect). One hypothesis for the problem-size effect is that larger arithmetic problems occur less frequently and therefore cannot simply be retrieved from long-term memory (Zbrodoff and Logan, 2005). As such, these problems must be actively computed, recruiting resources from the central executive. Another aspect of the relationship between mathematical problem solving and working memory involves the total number of steps required for problem solving. As with large number problems, problems with several operands cannot be solved via a simple retrieval process and must be solved through strategy- or procedure-based methods that rely more heavily on the central executive (Campbell and Xue, 2001).

The mathematical cognition community has worked to develop a process-based account for understanding the role of working memory in math problem solving and has identified specific processes that may be driving this relationship. Following the lead of this community, the geoscience cognition community would benefit from a similar approach. If one considers the working memory system to be essential for controlling attention and keeping relevant information active, multiple suggestions arise about how working memory capacity may contribute to learning in geosciences. From one perspective, referred to as the capacity account, it could be argued that successful learning in geoscience is contingent upon having enough resources for storing information while simultaneously processing other information (Wiley et al., 2011; Jarosz and Wiley, 2012). In the context of learning in geosciences, increased capacity could allow individuals to keep track of more objects, spatial transformations, perspectives, complex geometries of geological structure and landscapes, and so on. In the case of a complex geoscience task such as penetrative thinking (Kali and Orion, 1996), it could be argued that individuals who perform well on such tasks are better able to keep track of more layers and increasingly complex geometric shapes. Thus, block diagrams with more layers, faults, or folds may be more difficult largely because they rely more heavily on working memory. Individuals with low penetrative thinking skills may have less capacity for storing and maintaining complex spatial representations than individuals with high penetrative thinking skills and may benefit from instructional methods that allow working memory offloading.

Although there is no direct evidence for this perspective from the geosciences, some support comes from research on performance on spatial tasks, a construct highly related to working memory capacity (Marshalek et al., 1983). One study (Lohman, 1988) employed a complex mental-rotation task and varied the amount of time on the task and the degree of rotation (used to vary the complexity of the item—the greater the rotation, the greater the complexity). The results indicated that even with increasing amounts of time to complete the task, low-spatial participants could not exceed a certain level of accuracy as the problems increased in complexity. In addition, this threshold level of accuracy was lower for low-spatial individuals as compared to high-spatial individuals. Another study (Carpenter and Just, 1986) demonstrated that on the cube-comparison task, which requires mental rotation of a cube, low-spatial individuals tended to lose information about the cube stimuli after mentally rotating a particular side out of view. Together, these results support the idea that having enough capacity for storing and maintaining complex representations is essential for solving complex visual–spatial problems.

A second way that working memory may be related to performance on geoscience learning tasks is through the central executive, the component responsible for controlling attention and integrating information; this perspective is referred to as the attentional control account. Taken from work looking at the role of working memory capacity in tasks measuring general fluid intelligence, this perspective suggests that some individuals are better able to resist interference from old memories and to ignore distracting or irrelevant information (Wiley et al., 2011; Jarosz and Wiley, 2012). This increased ability to control one's attention could reduce the influence of previously encountered problems or scenarios, allow one to direct focus to relevant rather than irrelevant parts of a problem, and perhaps help the individual to develop novel ways of completing a task, ultimately allowing for more effective integration and mental model building. Using penetrative thinking as an example again, this perspective would predict that individuals who perform better are doing so because they are better able to resist proactive interference from previously encountered geological block diagrams. Specifically, as people progress through a set of geological block problems, there is interference from both previously encountered items and information from alternative-response options in the answer bank. Being able to ignore or inhibit information from previous problems, as well as being able to direct one's attention to relevant information and away from distracting information, may depend on the central executive component of the working memory system. The attentional control perspective might also predict that students who are high in working memory capacity would show less expectancy effects and be better able to handle new or novel information. For example, field geologists might expect their observations to fit a certain model, and if they are not able to, or simply do not attend to contradictory or novel information, they may be less likely to reject the incorrect model and form an updated and more accurate model of the area (Liben and Titus, 2012). It has been argued that attentional control, especially the ability to extract (segment) the key features and relationships in a complex visual field full of distractions, a process called disembedding, is one of the most important skills to learn in field geology (Reynolds, 2012). Essentially, by being able to focus on the most relevant information, extract key features from a complex visual field, and utilize new or novel information, high working memory capacity students may develop richer and more accurate mental models.

Again, although no data support this hypothesis specifically for geoscience, research on general fluid intelligence has demonstrated that successful performance may require better executive control. Specifically, Jarosz and Wiley (2012) found evidence in support of the attentional control account for the role of working memory capacity in performance on a nonverbal measure of fluid intelligence (Ravens Advanced Progressive Matrices). These studies found that individuals with high working memory capacity were less influenced by salient but incorrect distractors in the response bank than were individuals with low working memory capacity, such that low working memory capacity individuals spent more time looking at the salient distracters. These results indicate that individuals with low working memory capacity are especially susceptible to distraction and less able to control their attention. In addition, it has been shown that working memory capacity predicts performance on Raven's test, even after accounting for the variance common to long-term memory and short-term memory (Engle et al., 1999). This suggests that performance relies more heavily on the executive control component of working memory compared to a storage component.

Altogether, working memory could be affecting learning in geology through either of the major components of the working-memory system. Differences in the central executive component of the working memory system may contribute to learning in geology by allowing some individuals to more successfully inhibit irrelevant or distracting information within a problem in order to create an integrated mental model. However, differences in the storage component of the working memory system may allow some individuals to actively store more information, such as shapes, objects, transformations, and interactions between the geological structure and the land surface.

STRUCTURING GEOSCIENCE CLASSROOM ACTIVITIES AND CURRICULAR MATERIALS TO ACCOUNT FOR WORKING MEMORY AND COGNITIVE LOAD

The recognition of the importance of working memory issues and cognitive load leads to some overall recommendations about best practices in structuring classroom activities and designing curricular materials, whether they are handouts, course websites, laboratory exercises, or textbooks. Less clear is how to structure these activities and materials for individuals with different working memory capacities.

Research on working memory and cognitive load steers instructors away from long, uninterrupted lectures, where an unbroken string of information is presented. A clear implication of working memory research is that only a limited amount of new information can be held and processed at any one time, so instruction can and should be designed to explicitly account for this. Active learning is thought to be a better approach to learning (Freeman et al., 2014), and consideration of working memory and cognitive

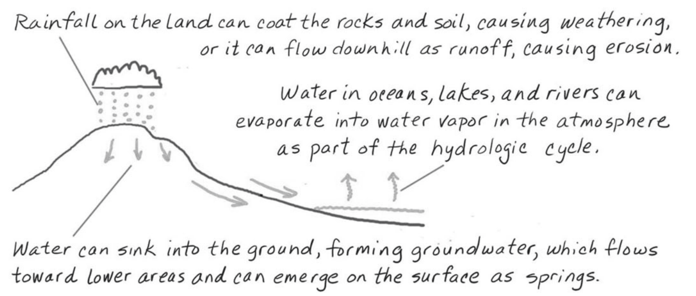


FIGURE 2: Simple example of a concept sketch of the hydrological cycle (from Reynolds et al., 2016).

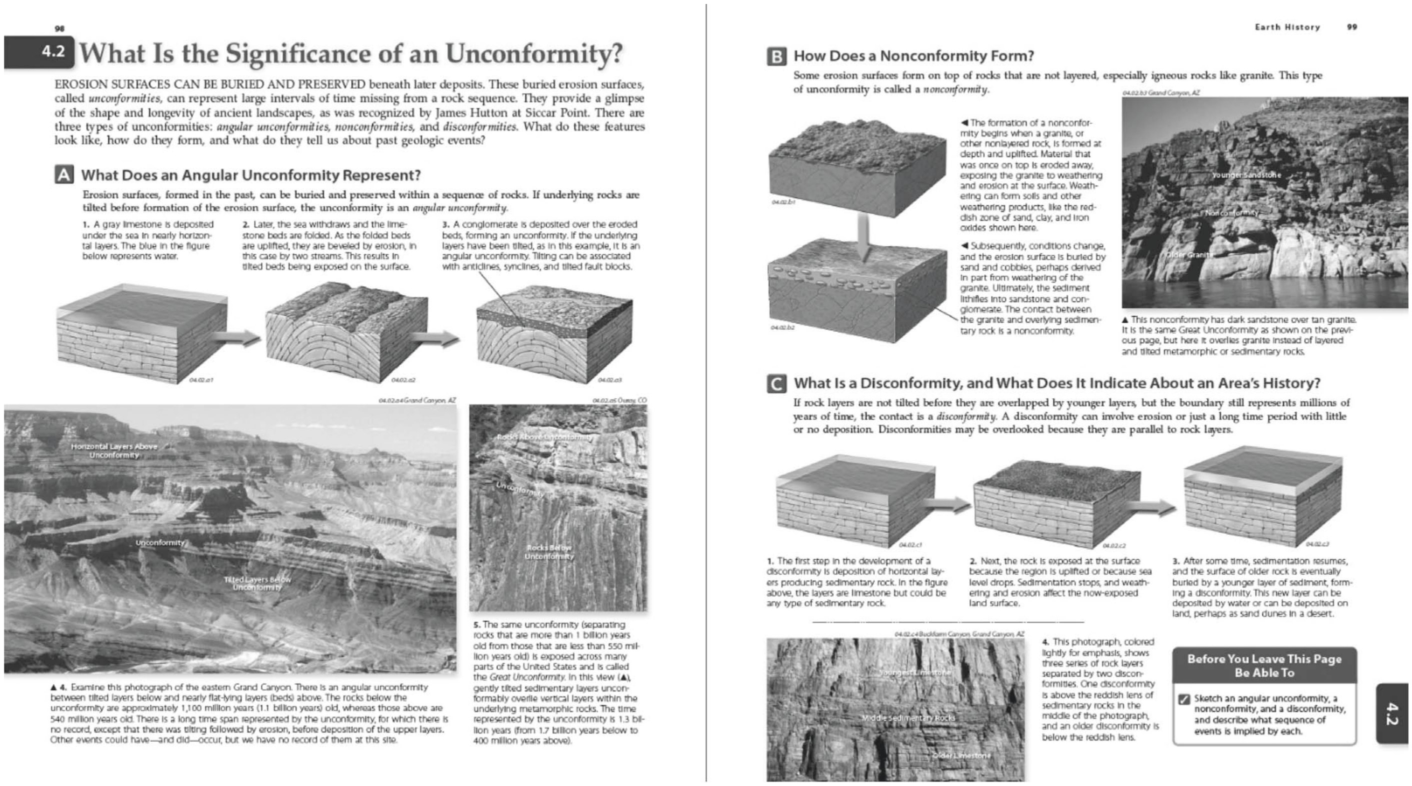
load help explain why. New information should be presented in relatively small chunks, so as not to overwhelm storage capacity. Active learning exercises allow the central executive to integrate the small chunks into a larger cognitive structure, which can be transferred to long-term memory. What counts as a chunk will vary with student's knowledge—as more content is stored, the size and complexity of a chunk will increase (Kimball and Holyoak, 2000). Unless there are breaks to allow students to consolidate and integrate the concepts and other information presented, much of any new information will not make its way into long-term memory. Consolidation exercises, such as a think-pair-share (MacDonald and Korinek, 1995) or minute papers (Angelo and Cross, 1993), are excellent ways to break up a long lecture, allowing students to start digesting new concepts. Explicitly decomposing complex information recognizes that working memory stores are of limited capacity and that an integration process needs to be utilized before these stores become overwhelmed and important information is lost or not integrated into the larger mental model.

Another activity that can support working memory is scaffolding (van de Pol et al., 2000), where simple concepts become a framework upon which later, perhaps more complex, concepts can be constructed. Through scaffolding, complex concepts are aggregated into a learner's mental framework, so that over time the size of a mental chunk grows, ideally providing an opportunity for adequate cognitive processing. Structuring lessons as a learning cycle or progression, where exploration proceeds introduction of terms and concepts, likely encourages simultaneous acquisition and processing of the new information and opens connections to existing knowledge frameworks (Lawson, 1995). Such opportunities for students to observe, interpret, discuss, and cognitively process geological features and processes can easily be interleaved within lectures (Reynolds and Peacock, 1998). This method highlights the important role of the central executive in the integration of information from dual stores. Integration does not happen automatically; therefore, scaffolding may support learning by guiding student's integration process. Even students who can store large amounts of information may struggle with trying to integrate that information into a single model. Scaffolding can provide students with a guide for what information to integrate and how to integrate correctly.

One consolidation approach that is particularly consistent with the principles of multimedia learning is to have students construct one or more concept sketches (Fig. 2). A concept sketch is a simple sketch annotated with complete sentences that describe features, processes, and interrelationships (Johnson and Reynolds, 2005). As such it employs a multimedia mix of a figure and text, with text closely linked (typically by leaders) to specific parts of a figure. The activity draws on the various ways scientists use sketching to help support reasoning about spatial aspects of concepts in geosciences (Tikoff, 2014; Gagnier et al., 2016) and the sciences more broadly (Ainsworth et al., 2011). A concept sketch requires learners to use both cognitive channels and stores within the working memory system (e.g., phonological loop and visuospatial sketchpad), facilitating deeper learning of geoscience concepts. Many geoscience courses currently deploy concept sketches for learning and assessment (Johnson et al., 2009). For example, an entire geomorphology course—lecture, lab, homework, and field trips—was redesigned around concept sketches, with impressive results (Reusser et al., 2012). Concept sketches may help to relieve some of the storage components of working memory, but they also provide students with a tangible representation of the propositional relations in their mental model. Offloading working memory by putting things onto paper relieves storage demands and facilitates integration by creating a singular representation that encompasses key elements. Although concept sketches can be used for formal assessment, they also provide opportunity for self-assessment and self-explanation, which can be important for updating long-term memory representations (Ainsworth and Loizou, 2003).

A working memory approach to diverse classroom activities can guide education design (McKeachie and Svinicki, 2006). The research by Mayer et al. (2001) suggests that out-loud narration of figures, the main activity in many lectures, is consistent with the principles of multimedia learning. Likewise, web pages accompanied by narration lead to more learning than do those with an overwhelming amount of text (Clark and Mayer, 2003). During narration of figures, textual information enters the brain via the ears and is held and rehearsed by the phonological loop, whereas simultaneously any images are sensed through our visual system and are held for processing by the visuospatial sketchpad. If the learner instead has to read words from a slide, then the text component and image have to compete for space in the visuospatial part of working memory. The redundancy principle (Mayer, 2005) suggests that including lengthy text, such as long bullet lists, containing the same information as the narration will actually decrease the amount of learning. The suggestion that long unbroken lectures be avoided also applies to explanations at the start of a lab class or introductory expositions before a field trip stop. In both these cases, the amount of information from a long verbal explanation will likely overwhelm the capacity of the working memory system and result in cognitive overload and decreased learning. Shorter, segmented, or scaffolded introductions in any setting are more consistent with the cognitive principles summarized in this paper. In sum, overloading the stores will overload the integration process. By removing redundant information, students can allocate more resources to integrating.

Printed curricular materials, such as textbooks, lab manuals, and handouts, can also be designed in a way consistent with the results of cognitive research. Figure 3 shows an example of geoscience material explicitly designed using the principles of multimedia learning and cognitive



98

4.2 What Is the Significance of an Unconformity?

EROSION SURFACES CAN BE BURIED AND PRESERVED beneath later deposits. These buried erosion surfaces, called *unconformities*, can represent large intervals of time missing from a rock sequence. They provide a glimpse of the shape and longevity of ancient landscapes, as was recognized by James Hutton at Siccar Point. There are three types of unconformities: *angular unconformities, nonconformities,* and *disconformities*. What do these features look like, how do they form, and what do they tell us about past geologic events?

A What Does an Angular Unconformity Represent?

Erosion surfaces, formed in the past, can be buried and preserved within a sequence of rocks. If underlying rocks are tilted before formation of the erosion surface, the unconformity is an *angular unconformity*.

1. A gray limestone is deposited under the sea in nearly horizontal layers. The blue in the figure below represents water.

2. Later, the sea withdraws and the limestone beds are folded. As the folded beds are uplifted, they are beveled by erosion, in this case by two streams. This results in tilted beds being exposed on the surface.

3. A conglomerate is deposited over the eroded beds, forming an unconformity. If the underlying layers have been tilted, as in this example, it is an angular unconformity. Tilting can be associated with anticlines, synclines, and tilted fault blocks.

04.02.a1 04.02.a2 04.02.a3

04.02.a4 Grand Canyon, AZ

▲ 4. Examine this photograph of the eastern Grand Canyon. There is an angular unconformity between tilted layers below and nearly flat-lying layers (beds) above. The rocks below the unconformity are approximately 1,100 million years (1.1 billion years) old, whereas those above are 540 million years old. There is a long time span represented by the unconformity, for which there is no record, except that there was tilting followed by erosion, before deposition of the upper layers. Other events could have—and did—occur, but we have no record of them at this site.

04.02.a5 Ouray, CO

5. The same unconformity (separating rocks that are more than 1 billion years old from those that are less than 550 million years old) is exposed across many parts of the United States and is called the *Great Unconformity*. In this view (▲), gently tilted sedimentary layers unconformably overlie vertical layers within the underlying metamorphic rocks. The time represented by the unconformity is 1.3 billion years (from 1.7 billion years below to 400 million years above).

Earth History 99

B How Does a Nonconformity Form?

Some erosion surfaces form on top of rocks that are not layered, especially igneous rocks like granite. This type of unconformity is called a *nonconformity*.

04.02.b1

◀ The formation of a nonconformity begins when a granite, or other nonlayered rock, is formed at depth and uplifted. Material that was once on top is eroded away, exposing the granite to weathering and erosion at the surface. Weathering can form soils and other weathering products, like the reddish zone of sand, clay, and iron oxides shown here.

04.02.b2

◀ Subsequently, conditions change, and the erosion surface is buried by sand and cobbles, perhaps derived in part from weathering of the granite. Ultimately, the sediment lithifies into sandstone and conglomerate. The contact between the granite and overlying sedimentary rock is a nonconformity.

04.02.b3 Grand Canyon, AZ

▲ This nonconformity has dark sandstone over tan granite. It is the same Great Unconformity as shown on the previous page, but here it overlies granite instead of layered and tilted metamorphic or sedimentary rocks.

C What Is a Disconformity, and What Does It Indicate About an Area's History?

If rock layers are not tilted before they are overlapped by younger layers, but the boundary still represents millions of years of time, the contact is a *disconformity*. A disconformity can involve erosion or just a long time period with little or no deposition. Disconformities may be overlooked because they are parallel to rock layers.

04.02.c1 04.02.c2 04.02.c3

1. The first step in the development of a disconformity is deposition of horizontal layers producing sedimentary rock. In the figure above, the layers are limestone but could be any type of sedimentary rock.

2. Next, the rock is exposed at the surface because the region is uplifted or because sea level drops. Sedimentation stops, and weathering and erosion affect the now-exposed land surface.

3. After some time, sedimentation resumes, and the surface of older rock is eventually buried by a younger layer of sediment, forming a disconformity. This new layer can be deposited by water or can be deposited on land, perhaps as sand dunes in a desert.

04.02.c4 Buckfarm Canyon, Grand Canyon, AZ

4. This photograph, colored lightly for emphasis, shows three series of rock layers separated by two disconformities. One disconformity is above the reddish lens of sedimentary rocks in the middle of the photograph, and an older disconformity is below the reddish lens.

Before You Leave This Page Be Able To

- Sketch an angular unconformity, a nonconformity, and a disconformity, and describe what sequence of events is implied by each.

4.2

FIGURE 3: Example textbook excerpt designed according to multimedia learning principles (from Reynolds and Johnson, 2015).

load. These pages feature inclusion of a figure for every important concept (to support the working memory system integrating abstract conceptual and visual information), tight integration of text and figures (spatial contiguity principle), elimination of redundant text (no columns of text and figure captions), no extraneous stories (coherence principle), and delimiting material into discrete blocks (e.g., two-page spreads and subsections) to limit cognitive overload. The design principles align to facilitate the central executive's integration of the key concepts into a coherent mental model. Imagine you are a student reading this same information as columns of text that are separated from the figures and being forced to jump back and forth from text to figures, perhaps several pages apart. Clearly, it is less cognitively demanding to digest the information in integrated text and figures, and eye tracking studies with such material support this and document increased student learning compared to traditional material arranged in long columns of text (Busch et al., 2010b). As summarized earlier, research in other disciplines implies that such materials would especially help students with low working memory capacity, but this has not been directly tested and is an important next step in developing evidence-based design practices.

An important issue in course design and implementation is that some people have more working memory capacity than others (Engle, 2002). Typically, the more working memory capacity a person has, the better that person's performance on academic tasks, such as problem solving and reasoning (Engle, 2002) and the better he or she is at learning with complex materials such as multimedia (Wiley et al., 2014). Thus, one might imagine that those with higher working memory capacity would be best equipped to deal with the difficulties associated with complex geological learning materials. However, individuals with lower working-memory capacity are thought to have limited capacity for processing complex material to begin with, which means that the demands of complex tasks required in geology may shrink this available capacity below the level needed to successfully solve difficult or novel problems. Thus, it follows that supporting effective integration of complex concepts will broadly support student learning.

DIRECTIONS FOR FUTURE GEOSCIENCE EDUCATION RESEARCH

Future work in the geoscience education research community should move toward developing a science of learning program that focuses on the role of working memory in science education. Based on findings from well-developed science of learning research programs in areas such as mathematics and physics, we identify a few priorities for future investigation in the geosciences. In particular, these priorities aim to provide the community with specific teaching and learning strategies for geoscience instructors that may take into account working memory.

Some instructional strategies are more or less effective for particular individuals depending on their specific abilities (Snow, 1989)—this concept is referred to as aptitude by treatment interactions (ATIs). The ATI framework suggests that optimal learning can occur when the instruction is matched to the aptitude or ability level of the learner. Highly structured or scaffolded treatments may be optimal for low-ability or low-knowledge students, whereas low structured or minimally scaffolded treatments may be best for high-ability or high-knowledge students (Snow, 1989). Identifying potential ATIs for working memory is critical for evaluating any material designed to support working memory. As geoscience educators and researchers continue to investigate methods for improving learning in their courses, collaborative efforts should be made to include cognitive skills measures in their designs. By including measures of working memory capacity and other cognitive skills, such as spatial thinking, the community can begin to identify students that need the most support and implement teaching and learning strategies that are most effective for these individuals. In addition, the community can begin to more clearly identify which consolidation approaches (i.e., sketching, gesturing, modeling, etc.) are best for offloading working memory and supporting integration processes.

An important conclusion from our consideration of working memory and cognitive load is the following: students with low working memory capacity are those least likely to learn from traditional classrooms that are dominated by long, continuous lectures without consolidation breaks or other opportunities for integration. Such instruction often overwhelms these students' working memory capacity, overloading stores and the central executive. In contrast, instruction that features active learning and consolidation exercises may allow students with low working memory capacity to self-regulate so that they are less likely to experience cognitive overload and therefore are more likely to learn. In other words, well-structured active learning may be most beneficial to those students who are most challenged by STEM courses.

Another potential direction for future research is to consider the role of expertise and cognitive skills in geoscience learning. While working memory is important in many every-day and academic endeavors, it is not necessarily required for all cognitive operations. For example, making your favorite recipe may be carried out with little or no reliance on working memory, because it can be completed in a fairly automatic fashion and the basic steps can be retrieved almost effortlessly from memory. The working memory system is needed, however, when new or current task goals conflict with these automatic processes. For instance, if you are missing an ingredient it may require you to alter the original recipe. In this case, it is important to keep the task goal actively maintained in order to override the automatic response of making the original recipe. If maintenance of the goal is lost, it is likely that one could be halfway through the wrong recipe before realizing it. In this example and more broadly, working memory is engaged when control is needed to overcome automatic tendencies. More specifically, working memory is needed when maintaining new or novel information is critical for completing an activity. This may be even more critical when there is considerable distraction, either external (e.g., a noisy classroom full of other students) or internal (e.g., thoughts about an upcoming exam in another class).

Research on the relationships among spatial skills, working memory, and disciplinary reasoning skill in experts has found little relationship between spatial skill and disciplinary skill and between working memory and disciplinary skill (Hambrick et al., 2012). This finding suggests that when a disciplinary skill is well learned (e.g., geological mapping), general cognitive resources may not be the principle determinant of how well an expert performs on the task. However, this does not mean working memory and spatial thinking are irrelevant—they are likely to play a role when the expert is working on a novel problem. The implication here is that the same strategies for supporting working memory, such as offloading working memory with sketches, gesturing, and models, could be employed to support disciplinary discovery. This suggestion highlights the opportunity for geoscience education to build upon prior work on spatial thinking skills, another important individual difference variable, to understand how the complex spatial and spatiotemporal processes are understood and reasoned about.

Here, we focus on learning as the interplay of cycles that construct understanding and the role of the mind in that process. We are confident that individual differences in capacity are important for educational design. Subtle design decisions may be guided by a detailed understanding of the nature of working memory processes. For example, there appear to be separable spatial and verbal working memory processes. Both types are surely relevant for science learning. As the role of working memory in geoscience learning becomes clearer, we anticipate a cycle of research and development that is informed by, and in turn will inform, cognitive science's theories of working memory.

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REFERENCES

Adams, J.W., and Hitch, G.J. 1997. Working memory and children's mental addition. *Journal of Experimental Child Psychology,* 67:21–38.

Ainsworth, S., and Loizou, A.T. 2003. The effects of self-explaining when learning with text or diagrams. *Cognitive Science,* 27:669–681.

Ainsworth, S., Prain, V., and Tytler, R. 2011. Drawing to learn in science. *Science,* 333:1096–1097.

Alloway, T.P., and Alloway, R.G. 2010. Investigating the predictive roles of working memory and IQ in academic attainment. *Journal of Experimental Child Psychology,* 106:20–29.

Alloway, T.P., Gathercole, S.E., Adams, A.M., Willis, C., Eaglen, R., and Lamont, E. 2005. Working memory and phonological awareness as predictors of progress towards early learning goals at school entry. *British Journal of Developmental Psychology,* 23:417–426.

Alloway, T.P., Gathercole, S.E., Kirkwood, H., and Elliott, J. 2009. The cognitive and behavioral characteristics of children with low working memory. *Child Development,* 80:606–621.

Alloway, T.P., and Passolunghi, M.C. 2011. The relationship between working memory, IQ: and mathematical skills in children. *Learning and Individual Differences,* 21:133–137.

Anderson, U. 2007. The contribution of working memory to children's mathematical word problem solving. *Applied Cognitive Psychology,* 21:1201–1216.

Angelo, T.A., and Cross, K.P. 1993. Classroom assessment techniques: A handbook for college teachers. San Francisco, CA: Jossey-Bass.

Antonenko, P.D., and Niederhauser, D.S. 2010. The influence of leads on cognitive load and learning in a hypertext environment. *Computers in Human Behavior,* 26:140–150.

Atkinson, R. 2005. Multimedia learning of mathematics. *In* Mayer, R., ed., The Cambridge handbook of multimedia learning. New York: Cambridge University Press, p. 393–408.

Ayres, P. 2006. Using subjective measures to detect variations of intrinsic cognitive load within problems. *Learning and Instruction,* 16:389–400.

Baddeley, A. 2000. The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, 4:417–423.

Baddeley, A.D., and Hitch, G. 1974. Working memory. *Psychology of Learning and Motivation,* 8:47–89.

Baddeley, A.D., Thomson, N., and Buchanan, M. 1975. Word length and the structure of short-term memory. *Journal of Verbal Learning and Verbal Behavior,* 14:575–589.

Banas, S., and Sanchez, C.A. 2012. Working memory capacity and learning underlying conceptual relationships across multiple documents. *Applied Cognitive Psychology,* 26:594–600.

Benton, S.L., Kraft, R.G., Glover, J.A., and Plake, B.S. 1984. Cognitive capacity differences among writers. *Journal of Educational Psychology,* 76:820–834.

Bull, R., and Scerif, G. 2001. Executive functioning as a predictor of children's mathematics ability: Inhibition, switching, and working memory. *Developmental Neuropsychology,* 19:273–293.

Busch, M.M., Coyan, J.A., and Reynolds, S.J. 2010a. Exploring how text–figure configuration affects introductory geology student learning behavior using eye-tracking technology. *In* Holscher, C., Shipley, T.F., Olivetti Belardinelli, M., Bateman, J., and Newcombe, N.S., eds., Proceedings of Spatial Cognition 2010. Mt. Hood, OR. Berlin, Germany: Springer-Verlag.

Busch, M.M., Coyan, J.A., and Reynolds, S.J. 2010b. Using eye tracking to explore how the spatial arrangement of text and figures influences geology learning. *In* Geological Society of America Abstracts with Programs, National Meeting, Paper 76-1.

Campbell, J.I., and Xue, Q. 2001. Cognitive arithmetic across cultures. *Journal of Experimental Psychology: General,* 130:299–315.

Cantor, J., Engle, R.W., and Hamilton, G. 1991. Short-term memory, working memory, and verbal abilities: How do they relate? *Intelligence,* 15:229–246.

Carlson, R., Chandler, P., and Sweller, J. 2003. Learning and understanding science instructional material. *Journal of Educational Psychology,* 95:629–640.

Carpenter, P.A., and Just, M.A. 1986. Spatial ability: An information processing approach to psychometrics. *Advances in the Psychology of Human Intelligence,* 3:221–253.

Chandler, P., and Sweller, J. 1991. Cognitive load theory and the format of instruction. *Cognition and Instruction,* 8:293–332.

Chen, W.C., and Whitehead, R. 2009. Understanding physics in relation to working memory. *Research in Science and Technological Education,* 27:151–160.

Clark, R.C., and Mayer, R.E. 2003. E-learning and the science of instruction. San Francisco, CA: Jossey-Bass.

Conway, A.R.A., Cowan, N., Bunting, M.F., Therriault, D., and Minkoff, S. 2002. A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence,* 30:163–183.

Conway, A.R.A., and Engle, R.W. 1996. Individual differences in working memory capacity: More evidence for a general capacity theory. *Memory,* 4:577–590.

Conway, A., and Jarrold, C. 2008. Variation in working memory. New York: Oxford University Press.

Coyan, J.A., Busch, M.M., and Reynolds, S.J. 2010a. Teaching students to disembed geologic features through signaling: an eye-tracking study. Poster presented at the Geological Society of America National Meeting, Denver, CO, October 10–November 3, 2010, Paper 248-14.

Coyan, J.A., Busch, M.M., and Reynolds, S.J. 2010b. Using eye tracking to evaluate the effectiveness of signaling to promote dissembedding of geologic features in photographs. *In* Holscher, C., Shipley, T.F., Olivetti Belardinelli, M., Bateman, J., and Newcombe, N.S., eds., Proceedings of Spatial Cognition 2010. Mt. Hood, OR. Berlin, Germany: Springer-Verlag.

Daneman, M., and Carpenter, P.A. 1980. Individual differences in working memory and reading. *Journal of Verbal Learning and Verbal Behavior,* 19:450–466.

Daneman, M., and Merikle, P.M. 1996. Working memory and language comprehension: A meta-analysis. *Psychonomic Bulletin and Review,* 3:422–433.

Danili, E., and Reid, N. 2004. Some strategies to improve performance in school chemistry, based on two cognitive factors. *Research in Science and Technological Education,* 222:203–226.

De Smedt, B., Verschaffel, L., and Ghesquière, P. 2009. The predictive value of numerical magnitude comparison for individual differences in mathematics achievement. *Journal of Experimental Child Psychology,* 1034:469–479.

Dixon, P., LeFevre, J.A., and Twilley, L.C. 1988. Word knowledge and working memory as predictors of reading skill. *Journal of Educational Psychology,* 80:465–472.

Engle, R.W. 2002. Working memory capacity as executive attention. *Current Directions in Psychological Science,* 111:19–23.

Engle, R.W., Carullo, J.J., and Collins, K.W. 1991. Individual differences in working memory for comprehension and following directions. *Journal of Educational Research,* 845:253–262.

Engle, R.W., Tuholski, S.W., Laughlin, J.E., and Conway, A.R. 1999. Working memory, short-term memory, and general fluid intelligence: A latent-variable approach. *Journal of Experimental Psychology: General,* 1283:309–331.

Freeman, S.R., Eddy, S.L., McDonough, M., Smith, M.K., Okoroafor, N., Jordt, H., and Wenderoth, M. 2014. Active learning improves student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences,* 111(23):8410–8415.

Gagnier, K.M., Atit, K., Ormand, C.J., and Shipley, T.F. 2016. Comprehending 3D diagrams: Sketching to support spatial reasoning. *Topics in Cognitive Science*, 8(4):1–18. doi:10.1111/tops.12233.

Gathercole, S.E., Pickering, S.J., Knight, C., and Stegmann, Z. 2004. Working memory skills and educational attainment: Evidence from national curriculum assessments at 7 and 14 years of age. *Applied Cognitive Psychology,* 181:1–16.

Geary, D.C., Hoard, M.K., Nugent, L., and Bailey, D.H. 2012. Mathematical cognition deficits in children with learning disabilities and persistent low achievement: A five-year prospective study. *Journal of Educational Psychology,* 1041:206–223.

Ginns, P. 2006. Integrating information: A meta-analysis of the spatial contiguity and temporal contiguity effects. *Learning and Instruction,* 166:511–525.

Hambrick, D.Z., Libarkin, J.C., Petcovic, H.L., Baker, K.M., Elkins, J., Callahan, C.N., Turner, S.P., Rench, T.A., and LaDue, N.D. 2012. A test of the circumvention-of-limits hypothesis in scientific problem solving: The case of geological bedrock mapping. *Journal of Experimental Psychology: General,* 141:397–403.

Harp, S.F., and Mayer, R.E. 1997. The role of interest in learning from scientific text and illustrations: On the distinction between emotional interest and cognitive interest. *Journal of Educational Psychology,* 891:92–102.

Harp, S.F., and Mayer, R.E. 1998. How seductive details do their damage: A theory of cognitive interest in science learning. *Journal of Educational Psychology,* 903:414–434.

Hegarty, M., Shah, P., and Miyake, A. 2000. Constraints on using the dual-task methodology to specify the degree of central executive involvement in cognitive tasks. *Memory and Cognition,* 283:376–385.

Holmes, J., Adams, J.W., and Hamilton, C.J. 2008. The relationship between visuospatial sketchpad capacity and children's mathematical skills. *European Journal of Cognitive Psychology*. 202:272–289.

Jarosz, A.F., and Wiley, J. 2012. Why does working memory capacity predict RAPM performance? A possible role of distraction. *Intelligence,* 405:427–438.

Johnson, J.K., and Reynolds, S.J. 2005. Concept sketches: Using student- and instructor-generated, annotated sketches for learning, teaching, and assessment in geology courses. *Journal of Geoscience Education,* 531:85–95.

Johnson, J.K., Reynolds, S.J., Tyburczy, J., Busch, M.M., and Coyan, J.A. 2009. Resolving the breadth versus depth versus inquiry dilemma in introductory college geology courses. *In* Geological Society of America Abstracts with Programs, National Meeting, Paper 49-1.

Johnstone, A.H., Hogg, W.R., and Ziane, M. 1993. A working memory model applied to physics problem solving. *International Journal of Science Education,* 15:663–672.

Kail, R., and Hall, L.K. 2001. Distinguishing short-term memory from working memory. *Memory and Cognition,* 291:1–9.

Kali, Y., and Orion, N. 1996. Spatial abilities of high-school students in the perception of geologic structures. *Journal of Research in Science Teaching,* 334:369–391.

Kalyuga, S., Chandler, P., and Sweller, J. 1998. Levels of expertise and instructional design. *Human Factors: Journal of the Human Factors and Ergonomics Society,* 401:1–17.

Kastens, K.A., and Ishikawa, T. 2006. Spatial thinking in the geosciences and cognitive sciences: A cross-disciplinary look at the intersection of the two fields. *In* Manduca, C.A., and Mogk, D., eds., Earth and mind: How geologists think and learn about the earth. Geological Society of America Special Paper 413. Philadelphia, PA: Geological Society of America, p. 51–74.

Kimball, D., and Holyoak, K.J. 2000. Transfer and expertise. *In* Tulving, E., and Craik, F.I.M., eds., The Oxford handbook of memory. New York: Oxford University Press, p. 109–122.

Kozma, R., and Russell, J. 2005. Multimedia learning of chemistry. *In* Mayer, R.E., ed., Cambridge handbook of multimedia learning. New York: Cambridge University Press, p. 409–428.

Kyllonen, P.C., and Christal, R.E. 1990. Reasoning ability is little more than working-memory capacity? *Intelligence,* 144:389–433.

Kyllonen, P.C., and Stephens, D.L. 1990. Cognitive abilities as determinants of success in acquiring logic skill. *Learning and Individual Differences,* 22:129–160.

Lawson, A.E. 1995. Science teaching and the development of thinking. Belmont, CA: Wadsworth.

Lee, K., Ng: E.L., and Ng, S.F. 2009. The contributions of working memory and executive functioning to problem representation and solution generation in algebraic word problems. *Journal of Educational Psychology,* 1012:373–387.

Lee, H., Plass, J.L., and Homer, B.D. 2006. Optimizing cognitive load for learning from computer-based science simulations. *Journal of Educational Psychology,* 98:902–913.

LeFevre, J., DeStefano, D., Coleman, B., and Shanahan, T. 2005. Mathematical cognition and working memory. *In* Campbell, J.I.D., ed., Handbook of mathematical cognition. New York: Psychology Press, p. 361–377.

Liben, L.S., and Titus, S.J. 2012. The importance of spatial thinking for geoscience education: Insights from the crossroads of geoscience and cognitive science. *In* Kastens, K.A., and Manduca, C.A., eds., Earth and mind II: A synthesis of research on thinking and learning in the geosciences. Geological Society of America Special Paper 486. Charlotte, NC: Geological Society of America, p. 51–70.

Logie, R.H. 1995. Visuo-spatial working memory. Hillsdale, NJ: Erlbaum.

Logie, R.H. 2003. Spatial and visual working memory: A mental workspace. *Psychology of Learning and Motivation,* 42:37–78.

Lohman, D.F. 1988. Spatial abilities as traits, processes and knowledge. *In* Sternberg R.J., ed., Advances in the psychology of human intelligence, vol. 4. Hillsdale, NJ: Erlbaum, p. 181–248.

Lohman, D.F. 1996. Spatial ability and g. *In* Dennis, I., and Tapsfield, P., eds., Human abilities: Their nature and measurement. Mahwah, NJ: Erlbaum, p. 97–116.

Low, R., and Sweller, J. 2005. The modality principle in multimedia learning. *In* Mayer, R.E., ed., Cambridge handbook of multimedia learning. Cambridge, United Kingdom: Cambridge University Press, p. 147–158.

Lowe, R.K. 2005. Multimedia learning of meteorology. *In* Mayer, R.E., ed., The Cambridge handbook of multimedia learning. New York: Cambridge University Press, p. 429–446.

MacDonald, R., and Korinek, L. 1995. Cooperative learning activities in large entry-level geology courses. *Journal of Geological Education,* 43:341–345.

Marshalek, B., Lohman, D.F., and Snow, R.E. 1983. The complexity continuum in the radex and hierarchical models of intelligence. *Intelligence,* 72:107–127.

Mautone, P.D., and Mayer, R.E. 2001. Signaling as a cognitive guide in multimedia learning. *Journal of Educational Psychology,* 932:377–389.

Mayer, R.E. 2005. Principles for managing essential processing in multimedia learning: Coherence, signaling, redundancy, spatial contiguity and temporal contiguity principles. *In* Mayer, R.E., ed., Cambridge handbook of multimedia learning. New York: Cambridge University Press, p. 183–200.

Mayer, R.E., and Anderson, R.B. 1991. Animations need narrations: An experimental test of a dual-coding hypothesis. *Journal of Educational Psychology,* 834:484–490.

Mayer, R.E., and Anderson, R.B. 1992. The instructive animation: Helping students build connections between words and pictures in multimedia learning. *Journal of Educational Psychology,* 844:444–452.

Mayer, R.E., Heiser, J., and Lonn, S. 2001. Cognitive constraints on multimedia learning: When presenting more material results in less understanding. *Journal of Educational Psychology,* 931:187–198.

Mayer, R.E., and Jackson, J. 2005. The case for coherence in scientific explanations: Quantitative details can hurt qualitative understanding. *Journal of Experimental Psychology: Applied,* 111:13–18.

Mayer, R.E., Mautone, P., and Prothero, W. 2002. Pictorial aids for learning by doing in a multimedia geology simulation game. *Journal of Educational Psychology,* 941:171–185.

McKeachie W.J., and Svinicki, M. 2006. Problem-based learning: Teaching with cases, simulations, and games. *In* McKeachie, W.J., ed., McKeachie's teaching tips: Strategies, research, and theory for college and university teachers, 12th ed. Boston: Houghton Mifflin, p. 222–225.

Mishkin, M., and Ungerleider, L.G. 1982. Contribution of striate inputs to the visuospatial functions of parieto-preoccipital cortex in monkeys. *Behavioral Brain Research,* 61:57–77.

Mitra, R., McNeal, K.S., and Bondell, H.D. 2016. Pupillary response to complex interdependent tasks: A cognitive-load theory perspective. *Behavior Research Methods,* 48:1–15.

Miyake, A., Friedman, N.P., Rettinger, D.A., Shah, P., and Hegarty, M. 2001. How are visuospatial working memory, executive functioning, and spatial abilities related? A latent-variable analysis. *Journal of Experimental Psychology: General,* 1304:621–640.

Miyake, A., and Shah, P. 1999. Models of working memory: Mechanisms of active maintenance and executive control. New York: Cambridge University Press.

Moreno, R. 2004. Decreasing cognitive load for novice students: Effects of explanatory versus corrective feedback in discovery-based multimedia. *Instructional Science,* 321:99–113.

Moreno, R., and Mayer, R.E. 2000. A coherence effect in multimedia learning: The case for minimizing irrelevant sounds in the design of multimedia instructional messages. *Journal of Educational Psychology,* 921:117–125.

Mousavi, S.Y., Low, R., and Sweller, J. 1995. Reducing cognitive load by mixing auditory and visual presentation modes. *Journal of Educational Psychology,* 872:319–334.

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

Paas, F.G., van Merriënboer, J.J., and Adam, J.J. 1994. Measurement of cognitive load in instructional research. *Perceptual and Motor Skills,* 79:419–430.

Passolunghi, M.C., Vercelloni, B., and Schadee, H. 2007. The precursors of mathematics learning: Working memory, phonological ability and numerical competence. *Cognitive Development,* 222:165–184.

Pickering, S.J., and Gathercole, S.E. 2004. Distinctive working memory profiles in children with special educational needs. *Educational Psychology,* 243:393–408.

Renkl, A., Atkinson, R.K., Maier, U.H., and Staley, R. 2002. From example study to problem solving: Smooth transitions help learning. *Journal of Experimental Education,* 704:293–315.

Reusser, L.J., Corbett, L.B., and Bierman, P.R. 2012. Incorporating concept sketching into teaching undergraduate geomorphology. *Journal of Geoscience Education,* 601:3–9.

Reynolds, S.J. 2012. Some important aspects of spatial cognition in field geology. *In* Kastens, K.A., and Manduca, C.A., eds., Earth and mind II: A synthesis of research on thinking and learning in the geosciences. Geological Society of America Special Paper 486. Boulder, CO: Geological Society of America, p. 75–77.

Reynolds, S.J., Johnson, J.K., Morin, P.J., and Carter, C.M. 2015. Exploring geology, 4th ed. Dubuque, IA, McGraw-Hill Education, 672p.

Reynolds, S.J., Johnson, J.K., Piburn, M.D., Leedy, D.E., Coyan, J.A., and Busch, M.M. 2005. Visualization in undergraduate geology courses. *In* Gilbert, J.K., ed., Visualization in science education. Boston, MA: Kluwer Academic Publishers, p. 253–266.

Reynolds, S.J., and Peacock, S.M. 1998. Slide observations—Promoting active observation, landscape appreciation, and critical thinking in introductory geology courses. *Journal of Geoscience Education,* 46:421–426.

Reynolds, S.J., Piburn, M.D., Leedy, D.E., McAuliffe, C.M., Birk, J.P., and Johnson, J.K. 2006. The Hidden Earth-Interactive computer-based modules for geoscience learning. *In* Manduca, C., and Mogk, D., eds., Earth and mind: How geologists think and learn about the earth. Geological Society of America Special Paper 413. Philadelphia, PA: Geological Society of America, p. 171–186.

Rhodes, S.M., Booth, J.N., Campbell, L.E., Blythe, R.A., Wheate, N.J., and Delibegovic, M. 2014. Evidence for a role of executive functions in learning biology. *Infant and Child Development,* 231:67–83.

Sanchez, C.A., and Wiley, J. 2006. An examination of the seductive details effect in terms of working memory capacity. *Memory and Cognition,* 342:344–355.

Sanchez, C.A., and Wiley, J. 2014. The role of dynamic spatial ability in geoscience text comprehension. *Learning and Instruction,* 31:33–45.

Shah, P., and Miyake, A. 1996. The separability of working memory resources for spatial thinking and language processing: An individual differences approach. *Journal of Experimental Psychology: General,* 1251:4–27.

Snow, R. 1989. Aptitude-treatment interaction as a framework for research on individual differences in learning. *In* Ackerman, P., Sternberg, R., and Glaser, R., eds., Learning and individual differences. New York: Freeman, p. 13–59.

Stull, A.T., and Mayer, R.E. 2007. Learning by doing versus learning by viewing: Three experimental comparisons of learner-generated versus author-provided graphic organizers. *Journal of Educational Psychology,* 994:808–820.

Swanson, H.L., and Jerman, O. 2006. Math disabilities: A preliminary meta-analysis of the published literature on cognitive processes. *Advances in Learning and Behavioral Disabilities.,* 19:285–314.

Sweller, J. 1988. Cognitive load during problem solving: Effects on learning. *Cognitive Science,* 122:257–285.

Sweller, J. 1994. Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction,* 44:295–312.

Sweller, J., Ayres, P., and Kalyuga, S. 2011. Measuring cognitive load. *In* Sweller, J., Ayers, P., and Kalyuga, S., eds., Cognitive load theory. New York: Springer New York, p. 71–85.

Taber, K.S. 2013. Revisiting the chemistry triplet: Drawing upon the nature of chemical knowledge and the psychology of learning to inform chemistry education. *Chemistry Education Research and Practice,* 14:156–168.

Tarmizi, R.A., and Sweller, J. 1988. Guidance during mathematical problem solving. *Journal of Educational Psychology,* 804:424–436.

Tikoff, B. 2014. Sketching in the Geosciences. Talk presented at a special workshop on Sketching in Science Education. May, Chicago, IL.

Tillman, C., Eninger, L., Forssman, L., and Bohlin, G. 2011. The relation between working memory components and ADHD symptoms from a developmental perspective. *Developmental Neuropsychology,* 362:181–198.

Toll, S.W., and Van Luit, J.E. 2013. Accelerating the early numeracy development of kindergartners with limited working memory skills through remedial education. *Research in Developmental Disabilities,* 34:745–755.

Unsworth, N., and Engle, R.W. 2007. The nature of individual differences in working memory capacity: Active maintenance in primary memory and controlled search from secondary memory. *Psychological Review,* 1141:104–132.

van de Pol, J., Volman, M., and Beishuizen, J. 2010. Scaffolding in teacher–student interaction: A decade of research. *Educational Psychology Review,* 223:271–296.

van Gog, T., and Jarodzka, H. 2013. Eye tracking as a tool to study and enhance cognitive and metacognitive processes in computer-based learning environments. *In* Azevedo, R., and Aleven, V., eds., International handbook of metacognition and learning technologies. New York: Springer New York, p. 143–156.

Vicari, S., Bellucci, S., and Carlesimo, G.A. 2006. Evidence from two genetic syndromes for the independence of spatial and visual working memory. *Developmental Medicine and Child Neurology,* 4802:126–131.

Wiley, J., Ash, I.K., Sanchez, C.A., and Jaeger, A. 2011. Clarifying goals of reading for understanding from expository science text. *In* McCrudden, M.T., Magliano, J.P., and Schraw, G., eds., Text relevance and learning from text. Charlotte, NC: Information Age, p. 353–374.

Wiley, J., Sanchez, C.A., and Jaeger, A.J. 2014. The individual differences in working memory capacity principle in multimedia learning. *In* Mayer, R.E., ed., The Cambridge handbook of multimedia learning. New York: Cambridge University Press, p. 598–619.

Zbrodoff, N.J., and Logan, G.D. 2005. What everyone finds: The problem-size effect. *In* Campbell, J.I.D., ed., Handbook of mathematical cognition. New York: Psychology Press, p. 331–345.