The following is a pre-publication draft of the article:

"Do we need to memorize that?" Or Cognitive Science for Chemists

that has been published online by the journal Foundations of Chemistry. The final publication is available online at Springer via http://dx.doi.org/10.1007/s10698-015-9226-z

"Do we need to memorize that?" *Or* Cognitive Science for Chemists

AUTHORS

JudithAnn R. Hartman,* Eric A. Nelson†

*Department of Chemistry, United States Naval Academy, Annapolis, MD 21042 USA

†Fairfax County Public Schools (retired)

ABSTRACT

In introductory chemistry courses, should students be encouraged to solve problems by reasoning based on conceptual understanding or by applying memorized facts and algorithms? Cognitive scientists have recently studied this issue with the assistance of new technologies. In the current consensus model for cognition, during problem solving the brain relies on "working memory" to sequentially process small elements of knowledge. Working memory is able to hold and manipulate virtually all elements that can be recalled "with automaticity" from long-term memory, but very few elements that are not recallable. As one consequence, students can reliably solve well-structured science problems only if most of the facts and algorithms needed to solve the problem have previously been well memorized. To achieve automaticity in recall, facts and procedures must be committed to memory (assimilated) and then tagged with associations to other knowledge (accommodated) in the brain's conceptual frameworks. Accommodation can be assisted by guided inquiry. Articles citing methods that can assist students in the development of automaticity are listed, and implications for chemistry instruction are discussed.

KEYWORDS
Chemical Education Research, Automaticity, Cognitive Science

CORRESPONDING AUTHOR: hartman@usna.edu

Learning Theories

By definition, "chemistry education" is multi-disciplinary: Work in our field calls for knowledge of (1) chemistry, and (2) how the student brain solves problems. However, for most instructors, our coursework has been more "in the discipline" than "about the brain." In part this may be because in chemistry there is much that is known with precision. Until recently, relatively little about the brain could be measured or stated with certainty.

For several decades, as scientific attention to cognition increased, a growing number of chemistry educators have explored cognitive psychology in search of instructional strategies to improve student learning. The theories of Swiss psychologist Jean Piaget (1896-1980) have frequently been cited for guidance. Piaget theorized that memory was organized in linked conceptual frameworks (each termed a schema) formed by the processes of "assimilation" (moving information into memory) and "accommodation" (modifying existing frameworks to incorporate new information) (Nurrenbern 2001).

A second facet of Piaget's theories proposed that young people progressed through stages of intellectual development, including a final transition to a "formal operational" stage where reasoning can be based on abstract concepts. According to Piaget, not all individuals reached this highest level, but many educators citing classical or modified Piagetian theories suggested that activities could help to move more students to this stage (Herron 1975, Bodner 1986; Cracolice 2005).

Beginning in the 1970's, scientists measuring cognitive activity proposed a substantial modification to the Piagetian theories. In this "information processing" model, reasoning is based on the interaction of two structures: A "long-term memory" (LTM) where information is stored and organized and "working memory" (WM) where information is processed (Clark et al. 2012). Seeking ways to help students solve problems in chemistry, studies based on this model have emphasized improving the organization of LTM (Johnstone 2010).

Since 1990, new technologies including functional magnetic resonance imaging (fMRI), positron emission tomography (PET), magnetoencephalography (MEG), and instruments to study eye movement have measured cognitive processes at scientific levels of precision. With an increase in verified data, past learning theories have been modified and a consensus has been reached among cognitive scientists on rules that govern how the brain solves some types of problems. One agreement is that nearly all children reach the stage of cognitive development where they are able to reason abstractly (Willingham 2008; National Research Council 2008; Anderson 2009).

In the current consensus model among cognitive scientists, problem solving is explained by the interaction of an LTM composed of conceptual frameworks and a WM where information is processed during thought (Willingham 2007; Anderson 2009). This model is detailed in textbooks for introductory cognitive psychology with a copyright date since 2006. Some components of the model with special relevance for chemistry instruction are provided below.

Long-Term Memory

In LTM, information is stored as elements of knowledge (small "chunks" of memorized facts, equations, or procedures) that are linked to form schema by a process of association similar to the accommodation mechanisms proposed by Piaget (Anderson and Lebiere 1998; Nurrenbern 2001, Willingham 2007).

As a result of natural selection, humans are biologically programmed so that a few types of learning are a focus of attention during "window periods" of development. A primary example is the acquisition of fluency in a spoken language prior to about age 12 (Pinker 2007). For types of knowledge that are not a focus of instinctive attention, including the facts and procedures of science, assimilation is initially resisted by LTM but can be reliably accomplished by repeated effort to recall new information spaced over multiple days. As new elements are encountered in different contexts, accommodation occurs. New associations modify frameworks and expand understanding (Anderson et al. 2000, Clark 2006, Clark et al. 2012).

Human LTM has enormous capacity. As one example, between birth and age 6, most children learn to comprehend between 8,000 and 16,000 words, and for a substantial percentage, they are able to apply hundreds of complex rules for use correctly, automatically, and effortlessly as they speak (Willingham 2007). By age 12, children can fluently recall twice as many words, plus thousands of other knowledge elements including names and images of people and places, events, facts and procedures of mathematics and science, and associations with sounds, odors, and textures. Only a small percentage of what we sense is incorporated into LTM, but if information is assimilated and accommodated, it can often be recalled for a lifetime (Anderson 2009, Clark et al. 2012).

Memory must be constructed at a gradual pace. As one example, between 18 months and first grade, even for the learning of language (which is powerfully instinctive), children typically learn the meaning of about 5-10 words per day (Willingham 2007).

Working Memory

In science, a primary goal is to solve problems. The brain solves problems in structures that taken together are termed working memory. WM can accept elements of knowledge from the environment, such as by listening or reading. If those elements have not previously been stored in LTM, they are termed "novel" elements. WM can also recall elements from LTM. What is termed thought, reasoning, planning, or problem solving is accomplished by the sequential processing of elements by WM (Anderson 2009; Clark et al. 2012).

During processing, WM can hold and manipulate an essentially unlimited number of elements that can be recalled from LTM "with automaticity" (quickly and accurately) based on cues and associations (Ericsson and Kintsch 1995).

However, when processing knowledge that has not previously been stored in LTM, WM is severely limited in both duration and capacity. Novel elements can be held in WM for only 30 seconds or less unless rehearsed (Peterson and Peterson 1959). In 1956, Miller famously noted that the number of "chunks" of novel knowledge that can be held in WM was "seven, plus or minus two," but in 2000 Cowan found that when knowledge is being manipulated during reasoning rather than simply being remembered, WM can hold only about 3-5 novel elements at any point in time (Cowan 2000, Miller 1956).

In subsequent studies, "3-5 chunks" and "30 seconds" were verified as being at the upper limits for novel elements that can held in WM at any point during problem solving. These capacities increase during childhood, decline in the elderly, and vary somewhat among individuals, but research indicates that there is no action you can take to significantly increase the capacity or duration of your novel WM (Cowan 2010; Clark et al. 2012).

To summarize: In the "working memory" where we solve problems, space for non-memorized information is minimal, but the ability to recall, hold, and apply previously well-memorized information is essentially unlimited.

Well- versus Ill-Structured Problems

Between 2006 and 2010, cognitive scientists vigorously debated the implications for teaching and learning of the limits quantified by Cowan for novel working memory (Kirschner et al. 2006; Tobias and Duffy 2009). As one outcome, among experts in cognition, since 2010 there has been general agreement about how students can most efficiently learn to solve many, but not all, of the types of problems encountered during pre-graduate-level courses in chemistry.

Cognitive science divides problems into two categories: "well-structured" and "ill-structured" (Simon 1973; Spiro and DeSchryver 2009). Well-structured problems are those in which experts in the discipline agree upon clear rules that apply, appropriate procedures to solve, and precise "right answers." Examples include most math problems, and in chemistry, problems including stoichiometry, solving algebraic relationships, or predicting the qualitative outcome of processes such as precipitation or oxidation-reduction.

Ill-structured problems come in several varieties. One is when a "right" answer is arguable among experts, as in many problems assigned in introductory courses in philosophy, literary interpretation, political science, and economics. In introductory chemistry, "Should our nation have a $4/Mg C carbon tax?" is a type of arguable ill-structured question that might be assigned in "Environmental Chemistry" or "Chemistry and Society" courses, or as part of a "science and society" unit in general chemistry for science majors.

A second type of ill-structured problem would be when a student is assigned a well-structured problem that they have not been taught to solve in a structured way, as when a new chemistry topic is introduced with an "inquiry" activity. For ill-structured problems, students might use a variety of general approaches to attempt to solve. These "heuristics" would include rules of thumb, trial and error, generalized reasoning or critical thinking strategies, and means-ends analysis (Willingham 2007).

Among cognitive scientists, there continues to be debate on the best methods to teach students to solve ill-structured problems. In contrast, there has been substantial agreement among cognitive scientists since 2010 for the limited case of how the brain solves well-structured problems and how students should prepare to solve such problems (Tobias and Duffy 2009).

In introductory "Chemistry for Science Major" courses, a central goal is to teach the procedures and strategies needed to solve quantitative and other rule-based problems that are frequently encountered in most scientific and engineering fields. Nearly all of the "end-of-chapter" questions in standard general and organic chemistry textbooks are well-structured.

Because these courses have relatively large enrollments and the cognitive science consensus is limited to well-structured problems, for the remainder of this paper we will limit our attention to well-structured problem-solving. Unless otherwise noted, a reference to a "problem" will mean the well-structured "end-of-chapter-type" problems in "science major" chemistry courses.

References for Educators

For educators, understanding how the student brain learns, how it solves problems, and what information it needs to solve problems is a central concern in our work. Experts in cognition have recently written a number of books and articles to assist instructors in exploring the implications of the new scientific consensus on problem solving. The following is a brief summary of publications that explore these issues with minimal technical jargon but extensive citation of primary sources.

1. A 4-page non-technical primer on how the brain solves problems is in the section "The Human Brain – Learning 101,"on pages 8-11 at http://www.aft.org/pdfs/americaneducator/spring2012/Clark.pdf

2. A 8-page summary focused on how the brain solves problems in the physical sciences and math is on pages 4-2 to 4-10 of *The Report of the Task Group on Learning Processes* in the *Final Report of the National Mathematics Advisory Panel* (NMAP) at https://www2.ed.gov/about/bdscomm/list/mathpanel/report/learning-processes.pdf

3. The important role of "automated" learning is summarized by Richard Clark on PDF pages 17-24 of "Not Knowing What We Don't Know" at http://www.cogtech.usc.edu/publications/clark_automated_knowledge_2006.pdf

4. The 2014 book *Make It Stick* by Brown, Roediger, and McDaniel reviews in detail college-level study strategies that build and organize LTM such as self-quizzing (including flashcards), summary sheets, interleaved practice, and elaboration.

5. For high school instructors, *Principles of Instruction* by Barak Rosenshine is a 9-page summary of structures for classroom instruction to maximize learning. http://www.aft.org/periodical/american-educator/spring-2012/principles-instruction

6. Columns in the *American Educator* by Daniel Willingham review cognitive research. Topics in science instruction are summarized in Post #10 at www.ChemReview.Net/blog . Willingham's *Why Don't Students Like School* is a 240 page paperback for under $15.

From those publications and others by cognitive experts, we have summarized below a number of on issues of particular interest in chemistry instruction.

The Importance of Automaticity

How can the impact of the limits on novel WM be minimized? The key strategy cited by cognitive researchers is "automaticity." In 2008, in the Report of the National Mathematics Advisory Panel (NMAP), a US presidential commission, David Geary, Valerie Reyna, Robert Siegler, Susan Embretson, and Wade Boykin advised,

> "At all ages, there are several ways to improve the functional capacity of working memory. The most central of these is the achievement of automaticity, that is, the fast, implicit, and automatic retrieval of a fact or a procedure from long-term memory." (Geary 2008).

There is also widespread agreement on what information must be automated. Daniel Willingham (2004) writes,

> "In each field, certain procedures are used again and again. Those procedures must be learned to the point of automaticity so that they no longer consume working memory space. Only then will the student be able to bypass the bottleneck imposed by working memory and move on to higher levels of competence."

Reviewing methodologies that have applied computer programming to model information processing by the brain, Richard Clark (2006) notes,

> "John Anderson's ACT-R model … makes a very compelling case that all effective applied knowledge must be proceduralized and automated in order to circumvent the limits on working memory…. Most (other researchers) reach a similar conclusion about the importance of the automaticity process."

Another way to express these findings: Unless students have thoroughly memorized the key facts and procedures that need to be applied to solve a problem, it is unlikely they will be able to solve.

Achieving Automaticity

Achieving automaticity requires first moving new elements into LTM, and then working with both new and existing elements in a variety of contexts to develop associations (linkages) within the brain's conceptual frameworks (Anderson et al. 2000).

For non-experts (termed "novice" learners in a domain, which includes nearly all undergraduates), except for the limited topics of instinctive interest, achieving automated recall of new knowledge requires substantial effort. LTM can assimilate new elements in unfamiliar domains, but such learning generally requires repeated practice in the recall of facts and procedures spaced over several days. Variations of this learning strategy may be referred to as *retrieval practice*, *spaced overlearning* and application of the *testing effect* (Geary et al. 2008; Willingham 2009; Brown et al. 2014).

For automaticity to be effective, information must be recalled from the vast storehouse in LTM at appropriate times. To gain understanding of when knowledge is needed and when it is not, new stored elements must be applied during practice in problem solving so that the brain will associate a range of context cues with each new element. Study strategies that include *interleaved practice, reflection, elaboration*, and *faded guidance* gradually promote the fluent (effortless, appropriate, automatic) recall of elements that supports an intuitive sense of the steps to take to solve a problem. There is substantial evidence that these strategies to promote assimilation and accommodation significantly improve student success in problem solving (Clark et al. 2012; Rosenshine 2012, Brown et al. 2014).

Willingham (2009) describes the central cognitive principle as "memory is the residue of thought." We best remember what we think about repeatedly. Elements that are processed in the context during thought become associations defining the meaning of knowledge in memory.

Concepts, Inquiry, and Sequence

Our initial focus on memorization should not be taken to suggest that concepts are unimportant. Concepts are essential as a way to organize memorized elements.

There are a variety of proposed models to explain and predict the behavior of LTM, but in nearly all cases LTM is described as having a "parallel processing" structure (Willingham 2007). A word or fact or algorithm in LTM might be linked to other elements based on what it sounds like, or looks like, or is symbolized, or where it is encountered, or when it happens in a sequence, or how it behaves, or by its semantic categories. Some elements are linked to more elements than others or have linkages with higher strengths. Those higher-level "concepts," such as "potential energy" or "3-D molecular models" or "the behavior of particulate models" in chemistry, help to organize conceptual frameworks into a "deeper" structure. Sensing a knowledge element (such as detecting the odor of ammonia) leads to activation of representations of that element in LTM (such as molecular or structural formulas), which activates linkages to associated facts and algorithms (such as gas at room temperature, lone pair, or basic aqueous solutions). Those elements are weighed depending on other context cues, selectively recalled into WM, and applied to solve problems.

However, before it can be conceptually organized, an element must first be moved into LTM by effort to recall its content. A concept does not create a procedure that solves a problem, but by gradually linking new elements within a conceptual framework, appropriate memorized procedures can be recalled for a wider variety of problems (Anderson et al. 2000).

Our discussion so far does not address whether or not there is a function for inquiry-based exercises. Research does show that inquiry activities can help both before and after initial work to assimilate new knowledge.

Achieving automaticity at recall of facts and procedures requires substantial effort, and strategies that promote recall, such as flashcards for self-testing, may not be pleasurable for most students. Inquiry that creates curiosity about a topic can motivate students to persist at the hard work of learning. (Duckworth et al. 2007) In addition, Schwartz et. al. (2011) note that guided inquiry to introduce a topic can prepare students to see deeper conceptual principles as they later work to automate factual recall. This initial inquiry, however, must be carefully monitored so that students do not "discover" misconceptions that they move into memory (Rosenshine 2012).

After students have practiced recall of new elements and practiced problems that apply that knowledge, active learning including demonstrations can help to create vivid associations that define meaning and identify the context in which new elements will likely be encountered. The frameworks that connect facts and algorithms must be constructed in the brain of each individual (Geary et al. 2008, Sweller 2009).

Findings of cognitive science suggest the following instructional sequence when introducing a new topic.

A. First, a short (10 minute) inquiry activity that involves the topic and its context.

B. A lecture or "lecture note handout" with frequent "clicker questions" that provoke thought about the meaning of new knowledge.

C. Study by students to commit new facts, equations, and procedures to LTM and practice their recall.

D. Interleaved practice that applies new knowledge to different types of problems.

E. Demonstrations and inquiry that tag new information with visual, auditory, and semantic associations.

In higher education, Steps A and E can be done during class time, while B-D can be completed during study time (as one form of "flipped" instruction).

Fluent Recall versus Reasoning

We have now arrived at our initial question: "Should students be encouraged to solve problems by reasoning based on conceptual understanding or by applying memorized facts and algorithms?" (In this usage, "algorithms" are procedures with sequenced steps to achieve a goal.) Experts in cognition say that during introductory courses, students should learn to solve well-structured problems using well-structured algorithms that are memorized until they can be recalled with automaticity.

When solving new problems, the brain relies primarily on recall of steps taken to solve prior problems which had similar cues and context elements (Anderson et al. 2000; Clark 2006). By definition, well-structured problems have procedures to solve that are rule-based and highly reliable. Learning these algorithms and when to apply them takes substantial practice, but the result is that in problems such as titration or gas law calculations, an appropriate algorithm or equation can be intuitively recalled, and if is applied without error, a precise right answer should result every time.

When algorithms become practiced to the point that they can be applied effortlessly, in cognitive science they are termed automated procedures. Generally, we are conscious of novel information being held in WM, but when knowledge is applied automatically from LTM we are often unconscious of doing so (Clark 2006).

Recalling procedures at appropriate times is a process the human brain evolved to support. When speaking, each of us fluently (unconsciously, effortlessly, quickly, intuitively, automatically) recalls and applies precise and appropriate words (facts) and rules for pronunciation, morphology, and syntax, and we do so at a rapid rate (Pinker 2007).

For learning not instinctive, such as solving mathematical or well-structured chemistry problems, the process is similar to initial language acquisition, but initial learning requires focused effort. Cognitive science recommends that teaching well-structured problem solving should include a structured sequence of clear, direct instruction in facts and algorithms, then extensive student practice in applying new knowledge to solve a variety of problems. The goal is that over time, facts and procedures are recalled automatically in a growing number of contexts. (Clark 2006; Brown et al. 2014)

Novice-Expert Differences

Cognitive science suggests that the strategy of having students solve problems by "thinking like a scientist" has inherent flaws. Science says that the novice brain simply cannot reliably solve well-structured problems in that manner.

Experts in a domain have a robust network of linked schema, organized by broad concepts. This allows them to assimilate new information more readily and to solve problems more quickly. By recognizing the deep structure of problems, experts can either fluently recall past procedures or construct mental models based on similar recalled situations. But to "solve problems like a scientist," students need the LTM of a scientist. That memory requires slow physiological changes, over years of study, for the brain to construct (Geary et al. 2008; Schwartz et al. 2011; Clark et al. 2012).

What results when novice learners try to reason with multiple elements of knowledge that are not well-memorized? During problem solving, the 3-5 novel element space must include the problem goal, the steps to solve if they are not well-memorized, where one is in the steps, and the data being processed at a given point. If that space becomes filled, a new novel element will replace a previously stored novel element. If a replaced element was needed during processing, the student becomes confused and unable to solve. As a result, novice learners nearly always must solve problems by applying *non*-novel facts and algorithms (Willingham 2004; Clark 2006; Clark et al. 2012).

Willingham (2004) suggests the following type of experiment to illustrate the impact of WM limitations. Secure blank paper and a pencil (or pen). Then, without using the pencil, calculator, fingers or toes, multiply 62 times 78 "in your head." Pick up the pencil only when you are ready to write your 4 digit answer. Try it. Allow two minutes.

Done? The confusion you experience, even for a simple 2 digits times 2 digits, demonstrates what students experience when asked to solve problems by reasoning when middle step answers are not well-memorized. Now try the problem using paper and pencil.

Success comes quickly with an algorithm designed to sequence processing and limit WM overload that, thanks to instruction, memorization, and practice, you were able to fluently recall from long ago.

In a paper arguing for the use of "constructivist" approaches when solving ill-structured problems, cognitive scientists Rand Spiro and Michael DeSchryver (2009) write:

> "In well-structured domains, we agree that concepts can be directly instructed, fully-explained, and simply supported – and more often than not they should be. Yes, the data favor direct instructional guidance, but most of this data is from well-structured domains like physics and mathematics….. It could be said that direct instructional guidance approaches have been validated for just those domains where essential information was most identifiable and full explanation most viable – i.e., where those approaches were most likely to work."

For the limited case of the well-structured problems in mathematics, physics, and chemistry, there is broad agreement among cognitive experts that students must learn to master well-structured procedures. When students cannot automatically recall a procedure to solve a well-structured problem, heuristics can be employed, but rules of thumb or trial and error strategies generally do not result in the high rate of success necessary for work in science, health, and engineering.

Understanding versus Fluency

In introductory courses, is "explicit understanding" important in learning? Only to a limited extent. For example, if you write "I bent one glass tube but broke the other," do you understand that you are using two of the relatively small number of the irregular verbs of English? Do you understand *why* bent and broke are the proper past tense of bend and break, though we may plea "on bended knee?"

For chemistry instructors, perhaps not. Yet since about age 5 you have likely been able to use bent and broke correctly whenever called for because your brain evolved to support intuitive, automated, implicit understanding. Linguistics majors need explicit understanding of those rules, but for you, English is a tool. A correct answer without detailed and explicit grammatical understanding is nearly always sufficient -- and achieved.

Even in the case of problem solving that is not instinctive, such as calculating the value for a variable in the Nernst equation, are you able to solve even without an explicit understanding of when you are using associative, commutative, or distributive properties? As a chemist, and for your non-math-major students, solving the algebra correctly in practice is what matters for most work.

In many respects, mathematics, chemistry, and physics are symbolic written languages in which fluency (implicit understanding) in applying facts (words) and rules (syntax) is required in the use of each language but explicit understanding is necessary only in areas of disciplinary expertise.

According to the National Science Foundation (2013), in 2010 only 0.74% of the bachelor's degrees awarded in the United States were in chemistry. Fifteen times more students (11.3%) majored in physics, engineering, biological, or agricultural sciences. For nearly all of those majors, a quantitative first-year chemistry course is required, serving as essentially an "introduction with a quantitative emphasis to problem solving in the physical sciences."

General/GOB students ask our help to become *fluent* in the wide variety of chemistry calculations that may be needed in their careers. With instruction and practice, students can reliably arrive at right answers to those chemistry-related problems in one or two semesters of study. Fluency requires practice but limited *explicit* ability to explain broad principles (Pinker 2007; Clark 2006). Being able to explicitly explain why a fact or procedure should be applied is a worthy goal, but the understanding expected of chemistry majors will be developed on upper level chemistry courses. This is understood by the American Chemical Society, which does not include freshman chemistry in the courses required for an ACS accredited degree.

Conclusion

Science instructors lead two lives. As educators, we are often passionate. As scientists, when views differ, our core belief is that all sides of an issue that have evidence to support them should be dispassionately evaluated based on what the data say. If beliefs conflict with science, in determining instructional policy, science must prevail.

The authors would suggest that if a question involves the content of chemistry, experts with research degrees in chemistry should be relied upon. On questions of how the consensus among cognitive scientists applies to a problem in teaching chemistry, instructors with a degree in chemistry would have a valuable perspective.

In our view, however, on a fundamental question of how the brain solves problems, to the extent there is a disagreement between the consensus of cognitive science and individuals with research degrees in the physical sciences, cognitive science should be relied upon. Respect for disciplinary expertise is a foundation for science. At any given time, "science" in a field is what the credentialed experts in that field agree it is.

Thomas Kuhn (1962) observed that in science, a new consensus is reached when experts in a field repeat assertions that have been debated, and few experts in the discipline object to those assertions. In learning to solve well-structured problems, as best the authors of this article can tell from our reading, over the past four years, no researcher in cognitive science has questioned the LTM/WM model, the necessity to memorize fundamentals to automaticity, or the value of carefully guided inquiry in constructing understanding. That said, we hope that our readers will challenge that finding if evidence to the contrary from cognitive experts can be found.

Discussion and debate on the meaning of research is always warranted, but we hope it will proceed with some urgency. As a percentage of U.S. bachelor's degrees awarded, between 1985 and 2010, chemistry degrees fell from 1.07% to 0.74%, a 31% decline. Together, degrees in physics, engineering, and chemistry fell from 9.2% to 5.5%, a 40% decline (National Science Foundation 2013).

Learning science must include the hard work of thorough memorization. That may not be a finding that we would prefer to hear, but cognitive scientists agree, based on quantified, verified data, that it is a necessary conclusion. In our view, students will benefit from the discussion by educators of what these data say. As instructors, we can better assist students in learning a scientific discipline by explaining how cognition works and by aligning our teaching with how the brain actually works and learns.

Notes

The authors declare the following competing financial interests: Eric Nelson has co-authored textbooks in chemistry.

REFERENCES

Anderson, J. R.: Cognitive Psychology and Its Implications. Worth, New York (2009).

Anderson, J. R., Reder, L. M., Simon, H. A.: Applications and misapplications of cognitive psychology to mathematics education. Texas Educational Review, 1(2) 29-49 (2000).

Anderson, J., Lebiere, C. (eds.): The Atomic Components of Thought. Mahwah, NJ: Erlbaum Publishers. (1998)

Bodner, G. M.: Constructivism: A theory of knowledge. J. Chem. Educ. 63, 873– 878 (1986).

Brown, P C., Roediger, H. L., McDaniel, M. A.: Make It Stick. Harvard University Press, Cambridge MA (2014).

Clark, R.: Not knowing what we don't know: Reframing the importance of automated knowledge for educational research. In G. Clareboutand and J. Elen (eds.) Avoiding Simplicity, Confronting Complexity. Sense Publishers, Rotterdam (2006).

Clark, R., Sweller, J., Kirschner, P.: Putting students on the path to learning: The case for fully guided instruction. Am. Educator, 36(1), 6-11 (2012).

Cowan N.: The magical mystery four: How is working memory capacity limited and why? Current Directions in Psychological Science 19: 51–57 (2010). http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2864034/ (accessed Aug 2014)

Cowan, N.: The magical number 4 in short-term memory: A reconsideration of mental storage capacity. Behavioral and Brain Sciences 24, 87-185 (2000).

Cracolice, M. S.: How students learn: Knowledge construction in college chemistry courses. In Pienta, N. J., Cooper, M. M., Greenbowe, T. J., (eds.) Chemists' Guide to Effective Teaching; pp. 12-27. Prentice Hall: Upper Saddle River, NJ (2005).

Duckworth, A., Peterson, C., Matthews, M., Kelly, D.: Grit: Perseverance and passion for long-term goals. Journal of Personality and Social Psychology, 92, 1087-2011 (2007).

Ericsson, K. A., Kintsch, W.: Long-term working memory. Psychological Review 102.2, 211-245 (1995).

Geary, D., et al.: The report of the task group on learning processes. In The Final Report of the National Mathematics Advisory Panel, pp. 4-2 to 4-10. US Dept. of Education (2008). https://www2.ed.gov/about/bdscomm/list/mathpanel/report/learning-processes.pdf Accessed 10 November 2014.

Herron, J. D.: Piaget for chemists. J. Chem. Educ. 52(3) 146-150 (1975).

Johnstone, Alex H.: You can't get there from here. J. Chem. Educ. 87.1: 22-29 (2010).

Kirschner, P., Sweller, J., Clark, R.: Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem based, experiential and inquiry-based teaching. Educational Psychologist 41, 75-86 (2006).

Kuhn, T. S.: The Structure of Scientific Revolutions. University of Chicago Press: Chicago, (1962).

Miller, G. A.: The magical number seven, plus or minus two: Some limits on our capacity for processing information. Psychological Review, 63(2) 81-97 (1956).

National Research Council: Taking Science to School. National Academies Press, (2008).

National Science Foundation: Science and Engineering Degrees: 1996–2010, Tables 5, 37, 38 (2013). http://www.nsf.gov/statistics/nsf13327/ (accessed Aug 2014)

Nurrenbern, S. C.: Piaget’s theory of intellectual development revisited. J. Chem. Educ. 78, 1107−1110 (2001).

Peterson, L., Peterson, M.: Short-term retention of individual verbal items. Journal of Experimental Psychology, 58, 193-198 (1959).

Pinker, S.: The Language Instinct: How the Mind Creates Language. HarperCollins, New York (2007).

Rosenshine, B.: Principles of instruction: Research-based strategies that all teachers should know. Am. Educ. 36(1), 1219 (2012)

Schwartz, D. L., Chase, C. C., Oppezzo, M. A., Chin, D. B.: Practicing versus inventing with contrasting cases: The effects of telling first on learning and transfer. Journal of Educational Psychology, 103(4), 759-777 (2011).

Simon, H. A.: The structure of ill-structured problems. Artificial Intelligence, 4, 181-201 (1973)

Spiro, R.J., DeSchryver, M.: Constructivism. In Tobias S., Duffy T. (eds.) Constructivist Instruction: Success or Failure? pp. 106-123. Routledge, New York (2009).

Sweller, J.: What human cognitive architecture tells us about constructivism. In Tobias S., Duffy T. (eds.) Constructivist Instruction: Success or Failure? pp. 127-143. Routledge, New York (2009)

Tobias, S., Duffy, T. (eds.): Constructivist Instruction: Success or Failure? Routledge, New York (2009).

Willingham, D. T.: Practice makes perfect—But only if you practice beyond the point of perfection. American Educator, 28(1), 31-33 (2004).

Willingham, D. T.: Cognition: The Thinking Animal. Pearson/Prentice Hall, (2007).

Willingham, D. T.: What is developmentally appropriate practice? Am. Educator, 32(2), 34-39 (2008).

Willingham, D. T.: Why Don't Students Like School: A Cognitive Scientist Answers Questions About How the Mind Works and What It Means For The Classroom. Wiley, (2009).

# # # # #