Working Memory Limits and Chemistry Instruction

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ABSTRACT

Scientists who study how the brain solves problems have recently reached agreement on a number of findings that apply to how students learn chemistry. Some of these discoveries may be surprising. One is that for students, knowledge of concepts and "big ideas" is not sufficient to solve most problems assigned in general chemistry. Because of stringent limitations in "working memory," which is where the brain solves problems, science has found that to reliably solve problems of any complexity, students must apply facts and algorithms that have previously been well memorized. To develop an intuitive sense of which fundamentals to recall when, students must solve problems that apply memorized fundamentals in a variety of distinctive contexts. Based on these findings, science has identified strategies that speed learning and assist in retention of chemistry. Experiments will be suggested by which instructors can test science-informed methodologies.

INTRODUCTION

By definition, chemistry education is-multi-disciplinary: a combination of the science of molecular behavior and cognitive science.

Cognitive science is the study of how the brain thinks, conducted by scientists from disciplines including neuroscience, cognitive and educational psychology, and evolutionary biology. A sub-discipline studies how the brain learns and how it solves problems. For chemistry educators, because offering guidance in learning to solve problems is central in our work, findings of cognitive science can be helpful.

In the past two decades, with assistance from new technologies,[1-3] cognitive experts have reached consensus on a number of principles that describe how the brain solves problems in chemistry, physics, and mathematics.[4,5] In 2017, neuroscientist Mark Seidenberg summarized, "Although we are far from understanding how the brain works, many of its fundamental properties are known."[6] These fundamentals hold the promise of transforming the basis of chemistry education from opinion-based theories to science-informed best practices.

1

For a number of years, the authors of this paper have been involved in an informal collaboration of higher education and Advanced Placement (AP) instructors seeking to apply cognitive science to improve general chemistry achievement. In previously published papers, those instructors have reported measured positive results.[7,8,9] Based on that experience, we believe that by applying findings of cognitive research, instructors can help students learn more chemistry, faster, with better retention.

However, even among scientists, the progress of science can be controversial.[10] When experiments yield unexpected findings, difficult questions must be asked about assumptions that have guided previous scientific work.

Prior to 1990, substantial memorization was accepted as a necessary part of learning chemistry. But with new technologies, as information became increasingly accessible, views on memorization changed for many educators. Reforms were proposed and often adopted based on the optimistic assumption that during problem solving, the brain could process new or looked up information as effectively as it processed information previously well-memorized.

Unfortunately, by about 2010, cognitive research had found that this assumption was mistaken. Because of evolved characteristics of the "working memory" where the brain solves problems, to solve the types of problems we assign in general chemistry, cognitive scientists found that reasoning of any kind is not likely to work except when it involves the application of previously very well-memorized facts and algorithms. As a result, some reform initiatives in chemistry education may need to be re-thought.[10]

However, cognitive research has also found many of the "active learning" strategies in recent reform proposals, when timed correctly, can promote both interest and long-lasting learning.

This paper will analyze recent findings of cognitive research. Where possible, we will cite summaries written by cognitive experts for educators that limit technical terminology. Those summaries will include extensive references to peer-reviewed studies. Our hope is to assist instructors in locating knowledge that can improve the alignment of instruction with cognitive science while retaining the best features of recent reform initiatives.

SCOPE

In this paper, many findings cited will be conclusions regarding how the brain solves problems that for a time were debated among cognitive experts[11] but have not been substantially contested among cognitive experts for the past ten years. By widely accepted definitions, such findings have become consensus science.[10]

Readers are invited, however, to fact-check how long the assertions we cite have been uncontested among experts who study the brain. At points readers believe our

interpretation of how this new science should be applied is arguable, challenge is also invited.

Except where noted, the scope of our topic will be limited to the following questions: When solving well-structured problems in general chemistry for science majors, what are the measured strengths and limitations of the brain's working memory? What are the implications of those characteristics? What strategies work around those limits? In the sections that follow, we will define those terms.

LEARNING

We learn by solving problems. In the sections below, the terms "learning" and "problem solving" will often be used interchangeably. The reason? Perhaps the most important confirmation of cognitive science about learning is: The brain learns by solving problems.

With help from new technologies, cognitive neuroscientists have gained the ability to observe and measure learning in the brain. As detailed below, science has found that **learning** is the process of adding small elements of new information to the brain's long-term memory (LTM), then wiring them to related elements. When do elements tend to be added to and/or connected within LTM? After an individual successfully solves a problem.

In brief: We learn (wire the brain) by solving problems. Applying new learning to solve new problems, we learn more. In part because the brain of our species has a large capacity to store and wire knowledge elements, we have the potential to solve very complex problems.

TYPES OF PROBLEMS

Cognitive science divides problems into two types. **Well-structured problems** have a specific goal, initial state, constraints, and precise right answers that can be found by structured procedures**.** Mathematic and scientific calculations are one example. Cognitive experts consider chemistry, mathematics, and physics to be overlapping subsets of the language of words and symbols adopted by science to model the physical universe. Within that language, according to cognitive experts, the brain solves problems in nearly all respects by the same rules.

All other types of problems are termed "ill-structured," including those for which right answers are not known or are debatable.[5,12]

In the United States each year, for each graduating chemistry major, about 15 students graduate in biological, health care, or engineering majors.[13] Nearly all students in those majors are required to pass a course in general chemistry.

To serve these majors, as widely adopted textbooks reflect, general chemistry is designed to address both molecular behavior and methods employed to solve well-structured problems encountered across the sciences. For questions in which science knows algorithms that,

when applied properly, result in accurate right answers, society expects chemists, engineers, and medical professionals to apply those proven methods rather than less-reliable "heuristics" (speculation).

Below we will summarize in bold and then detail findings that, according to cognitive experts, apply when solving well-structured problems in disciplines that include chemistry.

INSTINCTIVE AND NON-INSTINCTIVE LEARNING

Some learning is automatic; learning chemistry is difficult. Into the DNA of all animal species, powerful drives have been programmed by natural selection. Learning is one such drive. Each species has evolved to learn automatically for limited topics that assist with adaptation and survival in primitive and highly competitive environments. For those topics, the brain automatically stores in long-term memory knowledge gained from experience.[14-16]

As one example, our species is driven to learn sophisticated vocalized communication. Creating speech is a task of enormous cognitive complexity, yet human children learn thousands of rules required to speak the dialect of their clan with minimal explicit instruction in those rules. Instinctively, to solve the problem of learning to speak, children store in memory words they hear, subconsciously determine their meaning and rules for their use, then add the words to their spoken vocabulary.[14]

The human brain also automatically and subconsciously determines and stores complex rules for limited additional topics that assisted in prehistoric survival, including facial recognition, conventions of familial and social relationships, and a basic physics of how things work.[15,16]

Our brain has weaknesses as well. To focus on survival skills, other learning must be lower priority. As a result, for non-instinctive topics, moving knowledge into memory requires effort. Mathematics and chemistry are especially difficult. This is in part because, being primarily symbol rather than sound-based, few aspects are learned automatically,[15,16] and in part because their definitions are precise.[4] For example, English-speaking children automatically learn an operational definition of "temperature," but storing "temperature is a measure of the average kinetic energy of molecules" verbatim in memory requires repeated effort at recall.

COGNITIVE ARCHITECTURE

A central purpose of schooling is to supply citizens with skills in solving problems humans do not learn to solve automatically but modern societies need solved. According to science, to solve problems of any complexity, the brain must apply previously learned relationships to process problem data. The model science uses to explain learning is based

upon the brain's components and their characteristics: what cognitive researchers describe as the brain's "atomic" structure.[17]

Descriptions by cognitive scientists of how the brain solves problems include both observations of neuroscience and models from cognitive psychology that accurately predict experimental outcomes. The following will use terminology and explanations from both disciplines that are employed most often to describe learning.

Learning and problem solving involve three types of memory. The brain stores what an individual has learned in tens of billions of **neurons:** specialized cells in the brain's **long-term memory (LTM)**. Each neuron can store a small **element** of knowledge. After an element is stored, its neuron can grow thousands of **wires** that connect at **synapses** to neurons storing other elements.[6,18,19]

This structure gives human LTM an enormous capacity, but knowledge must be stored gradually. As one example, U.S. college graduates on average know the meaning of about 17,000 "root words" learned since infancy at a rate of 2-3 per day.[20]

Learning begins with attention. To solve a problem, the brain must first focus its **attention** on the problem's data.[4] Input collected by the senses is then **encoded**: decomposed into small elements the brain can store and process. Those elements move into the brain's **working memory**.[18,19,21]

Working memory is where problems are solved. For multi-step problems, answers are obtained by **information processing**: holding, manipulating, and integrating unique problem elements with previously learned facts and procedures in a stepwise process.[22,23]

Activated chunks are a third type of memory. Cognitive science defines a **chunk** as a subset of elements in LTM that are related and are connected by wiring among neurons.[6,21,24-26]

HOW PROBLEMS ARE SOLVED

Among cognitive experts there is broad agreement on a substantial number of rules that apply when solving well-structured problems.[4-6]

Cues prompt recall of chunks. During problem solving, as data elements enter working memory, the brain uses each element as a **cue** to search LTM for matching elements.[27] If a match is found, the LTM neuron holding the match **activates** ("fires") and sends an electrical signal to other elements to which it is wired (chunked). Depending on the strength of the signal, connected, related elements may also activate and fire.[6,18,21]

Linked, related elements that activate are said to be **recallable** into working memory by the cue. In working memory, relationships in activated, recallable chunks *plus* the novel problem data can be **integrated**: processed together to convert problem data step by step to reach the problem goal.[2,18,22,27] An example is converting "units to moles to moles to units."

To learn, solve problems successfully. How is a new element stored in LTM? How do its related elements become linked? Neuroscientist Efrat Furst explains, "processing in working memory is … information's 'entry ticket'" to LTM.[18]

If a step while solving a problem in working memory is "perceived as useful and successful,"[28] a record of elements processed at the step is stored in "temporary LTM." If these elements are repeatedly processed together during the next week or two, the relationships tend to become wired into "more permanent LTM."[29,30] The (simplified) adage of neuroscience is "Neurons that *fire* together, *wire* together."[31]

However, if similar problems are *not* solved several times over several days, the record of relationships applied while solving will tend to be lost.[18,29,32,33]

An example of wiring LTM is memorizing a word's definition. A word (a chunk of letters and a chunk of sounds) is defined in terms of known knowledge elements. By repeated practice at recall, the unfamiliar word and its meaning are processed together in working memory, the word is stored in LTM neurons, and its relationship to the elements in its definition become wired into LTM.[18,33] By a similar process, other fundamental relationships such as arithmetic facts and scientific equations can be made recallable.[34]

To learn, start by making fundamentals recallable. For each new topic, a primary student goal is to learn to solve multiple types of problems. To do so, an initial step is to make the relationships needed most often to solve problems *quickly recallable* from LTM in response to cues encountered in topic problems.[4,27]

Wire larger chunks by solving problems. After basic relationships are made recallable from LTM, more complex and conditional relationships can be wired by using new recallable fundamentals to solve additional problems that include varied cues and contexts. Solving "word problems" is one example, but cognitive processing during demonstrations and laboratory activities can also deepen understanding by wiring sensory elements including sounds, visual images, odors, textures, plus sequences of steps, into chunks.

As elements are repeatedly processed together, their wired connections become stronger: They activate more easily in similar contexts.[21,24,26] As the elements in chunks and information stored by their wiring increases, their cues and contexts can enable activation of more relationships useful in solving problems.[18,35]

Wire a conceptual framework. As new sub-topics are learned, the expanding chunks in LTM form a **conceptual framework** (also termed a **schema**) for a topic.[36] Elements and the strength of their wired connections provide the brain with an intuitive sense of *which* facts and procedures need to be recalled to solve a problem.[26,28,34] In addition, after a basic schema is wired, additional related information can be stored LTM with less effort.[18,34]

WORKING MEMORY LIMITS

A key discovery of recent cognitive research is that solving problems can be difficult until relationships needed frequently have been *very* well memorized. Understanding the conditions in which working memory is strong and is limited can help in designing instruction that improves student learning.

Working memory is limited in both duration and capacity. Working memory can be described as composed of **slots.** During problem solving, these slots must hold the novel (problem specific) data in a problem. Novel data can include the problem goal, initial problem data, steps to solve, answers found at middle steps, needed relationships that must be "looked up," and final answers.[2,12,24,37-40]

During problem solving, for the novel data moved into slots, two limits apply. First, storage in working memory is temporary. Each slot can retain a chunk of novel data for about 30 seconds or less during other processing.[41,42.] Second, at each problem step, working memory has only 3-5 slots that can hold chunks of novel information.[39,40]

If data are supplied from multiple senses, such as "dual coded" by providing both visual and auditory descriptions, a few additional slots may be available, but total novel slot capacity remains quite limited.[38,43]

Space for activated chunks is unlimited. Working memory has the limits described above, but it also has strengths. A key to understanding learning is this rule:

> In working memory, during problem solving, slots are *unlimited* for relationships that can quickly be recalled from LTM. For other types of data elements, space and holding time are *very* limited.

During cognitive processing, working memory has a strong ability to recall and apply information that is well understood: relationships that have previously been wired into the conceptual frameworks of an individual's LTM.

Kirschner, Sweller, and Clark summarize that working memory is "very limited in duration and capacity" when processing elements with limited relevant LTM connections, but "when dealing with previously learned information stored in long-term memory, these limitations disappear."[44]

Why natural selection results in any specific outcome is speculative, but one suggestion to explain working memory limits is: By limiting the flow of unfamiliar information from the environment into working memory and then via processing to LTM, change in LTM must be gradual. This allows time for careful consideration of changes in LTM. Care in consolidation of new information protects the stability of conceptual frameworks that support our mental well-being (see reference 11, page 136).

Working memory limits can cause problem solving to fail. One implication of the rules above is that for a given topic, if a student has moved many fundamental data elements into LTM and wired them to many other relevant data elements, substantial resources are available to solve problems. But what happens if the relevant chunks are few in number or limited in connections?

At steps of a problem, if a cue is supplied but its needed related elements must be looked up or calculated, novel working memory will need to hold both the cue and its non-recallable answer. In a complex problem, the limited slots for novel data may already be full. If this is the case, working memory is said to **overload.** This causes a data element that may be needed at later steps to be "bumped out:" lost from working memory slots. [18,21,22,33] When working memory overloads, Willingham writes, "thinking will likely fail."[45]

For example, when solving a problem, if "phosphate ion" is supplied but its needed formula must be looked up, the formula requires a novel working memory slot. If slots are already full, overload forces out a data element, and confusion may result at a later step. In contrast, if an ion name and formula relationship has been memorized as a quickly recallable chunk, the name and formula need only one slot, making overload less likely.

For situations in which the prior wiring of chunks by students is limited, Tracy Alloway and Susan Gathercole explain, (Ref. *38*, p. 134),

> [T]he capacity of working memory is limited, and the imposition of either excess storage or processing demands in the course of an on-going cognitive activity will lead to catastrophic loss of information from this temporary memory system.

Speed is also important during problem solving. Information well-memorized is recalled quickly, but having to look up an answer, even on the internet, takes time. Because storage in working memory is quite limited in duration, during a search, other novel problem information being held in slots tends to "time out" and be lost.

Working memory limits and their impact are not contested. As previously noted, neuroscience and cognitive psychology explain learning in ways that vary in terminology and detail. However, all current scientific descriptions of problem solving include space in working memory that is stringently limited for novel data and non-recallable relationships, but is essentially unlimited for relationships quickly recallable. [44,46]

WORKING AROUND THE LIMITS

Cognitive scientist Daniel Willingham describes working memory as "the bottleneck of the mind because there is a limited amount of space in working memory."[33] To speed a process, we focus our attention on widening (or working around) the "bottleneck." To guide students in addressing (or circumventing) the bottleneck in learning, cognitive

experts advise that we teach three major strategies: automaticity, chunking, and algorithms.

Gain automaticity in recall of fundamentals. For most instructors, the need to memorize relationships as a part of learning chemistry may not be unexpected. What may be surprising is how *thoroughly* science says fundamentals should be memorized. In a 2008 report, six of the nation's leading cognitive scientists advised (ref. *4*, p. 4-5):

> [T]here 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…. [I]n support of complex problem solving, arithmetic [fundamental] facts and fundamental algorithms should be thoroughly mastered, and indeed, over-learned, rather than merely learned to a moderate degree of proficiency.

To recall "with automaticity," facts and procedures must be *very* well memorized.

Overlearn by retrieval practice. Reliable **automated recall** requires **overlearning**, defined as "sustained practice, *beyond the point of mastery"* in recall of knowledge from LTM.[33] Overlearning begins with **retrieval practice** activities, such as flashcard use, practice writing from memory tables of relationships, and clicker questions.[33,47,48] Retrieval activities apply the **testing effect**: Recall is strengthened more by testing, including self-testing, than by highlighting or re-reading.[27,49,50]

In Willingham's widely-cited formulation, "memory is the residue of thought."[27,51] As an example, during a lecture (or reading assignment) that includes definitions of many new terms, a pause for "clicker questions" on those definitions can help to move new vocabulary from working memory into "temporary LTM." This storage can free space in working memory for additional new information, assisting with speech (or reading) comprehension.[18,24] In addition, the retrieval prompted by the clicker question is a first step toward wiring a new chunk in LTM.

Overlearning should be spaced. To promote wiring facts, procedures, and their linkages into "more permanent LTM," overlearning should be repeated over several days and periodically thereafter. This **spaced retrieval** is termed **distributed practice.**[29,32,48,52]

Practicing recall several times in one day (termed **massed practice** or **cramming**) can promote success on a test, but if crammed knowledge is needed again after a few weeks, it tends to require a repeat of intensive study.[52] In contrast, after spaced overlearning, forgetting may occur, but when needed later, quick recall can generally be restored with far less re-study.

During careers, work may change, but facts and procedures studied by spaced overlearning tend to be recallable, with occasional "refreshing of memory," for a lifetime.[32,33,53]

Wire improved chunks. As students overlearn new relationships, elements enter LTM and are wired to related elements. As those chunks are applied to solve varied problems, more elements are connected in LTM and their relationships become more clearly defined. These higher quality chunks promote improved recall of relevant problem-solving relationships.[23,24]

Learn effective algorithms. An **algorithm** (also called a **procedure)** is a "recipe" that solves a type of complex problem in a sequence of steps. Examples include sequences remembered by mnemonics, the standard algorithms of arithmetic and algebra, and the steps of a worked example.

Complex problems can have extensive novel data. Successful algorithms are tested, proven sequences that for a given type of problem, process data in steps that avoid overloading working memory at any step.[4,34,45] Most algorithms are designed to process data by quickly applying well-memorized relationships, circumventing the duration and capacity limits of working memory. To avoid overloading working memory, the steps of algorithms and the contexts in which they apply should be recallable with automaticity from LTM.[4]

Gaining automaticity in the recall of facts and procedures requires time and effort. John R. Anderson, a leader in research on cognitive processing, advises (ref. *25*, p 359)

> [A]cquiring competence is very much a labor-intensive business in which one must acquire one-by-one all the knowledge components.… We need to recognize and respect the effort that goes into acquiring competence.

For students, learning science is hard work, but it can be less difficult if we teach strategies recommended by science to work around working memory limits.

Algorithms are required for all but simple problems. What does working memory overload feel like? How do algorithms work around limits? Let's perform an experiment.

Try multiplying 84 times 78 "in your head." No fingers or pencil. Try for at least two minutes, *then* write down what you experienced.

Now try 84 times 78 again, this time using pencil and paper.

A standard algorithm you likely memorized long ago uses a pencil instead of working memory to store middle-step digits. Compared to "in your head," how well did using a pencil work?

When trying to reason without the pencil, did storing the middle-step digits cause other needed data to be bumped out or timed out of your working memory?

Two digits times two digits is relatively simple. Most general chemistry problems, of necessity to prepare for future science careers, are not simple.

Chemists understand the concepts of arithmetic, but when reasoning to solve a multi-step problem without an algorithm in a field in which you are not an "expert," the confusion you experienced will likely result.[9,31,32,45] Repeated failure is discouraging. Science-based strategies are likely to lead to success, which may be motivational for prospective science majors.

IMPLICATIONS FOR INSTRUCTION

With the arrival of the information age, memorization of facts and procedures was widely presumed to have become less important. As a result, a number of recent instructional reforms in chemistry have been proposed and in some cases adopted that assumed students could solve problems by reasoning that relies on looked up information, big ideas, explicit conceptual understanding, inquiry processes, and/or "thinking like a scientist."

Unfortunately, since 2010, the experts who study how the brain works have been in agreement that in fields we are not experts, solving complex problems without applying memorized facts and algorithms is simply not something the brain can manage.

In some cases, cognitive scientists have addressed directly why some of the post-1990 reforms proposed in chemistry may need to be re-examined.

Learn concepts, but store fundamentals first. Concepts are fundamental principles that categorize and explain knowledge, often within a hierarchical structure. Potential energy, conservation of energy, and conservation of matter are concepts with many topic subcomponents. Willingham writes, "conceptual knowledge refers to an understanding of meaning, … understanding *why*" something is true.

To learn a concept, at least some subcomponents of concept knowledge must be quickly recallable first. Willingham advises, "a teacher cannot pour concepts directly into students' heads. Rather, new concepts must build on something students already know."[34]

Reasoning works in topics learned automatically; mathematics and chemistry require algorithms. Because the human brain automatically stores and wires large quantities of social and survival-skill knowledge, we all become expert in many daily activities. As a result, it may seem that to solve problems, we can reason like an expert generally. But cognitive studies show that for the complex but well-structured problems that are the focus of pre-graduate-school chemistry, student reasoning without applying algorithms is not likely to reliably lead to correct answers.[24,54]

Willingham writes when students seem to solve complex problems with reasoning but without a recalled procedure, research nearly always finds "understanding is remembering in disguise."[55] Anderson summarizes, "one fundamentally learns to solve problems by mimicking examples of solutions."[25]

Learn to apply facts and algorithms "with automaticity." Some proposals for curriculum reform disparage algorithmic problem solving. Cognitive studies have established that, to the contrary, applying memorized algorithms "with automaticity" is necessary to solve complex problems – to avoid working memory overload.

Richard Clark notes that automated knowledge, which is often applied unconsciously, "allows us to circumvent limits on conscious thinking …. while leaving working memory space to process the novel components of tasks."[28]

Being able to apply facts and procedures quickly and accurately, without conscious thought, is a goal of mastering any complex task. It requires substantial practice. [25,28]

Students cannot solve by "thinking like a scientist." Experts can often solve complex problems by reasoning without an algorithm. However, as Willingham writes, "No one thinks like a scientist … without a great deal of training…. Real scientists are experts…. [Y]ears of practice make a qualitative, not quantitative, difference in the way they think…."[56] Kirschner and Hendrick advise, "Beginners aren't 'little' experts."[36]

For the discipline in which one specializes, constructing the vast conceptual framework of an expert generally requires about 10 years of increasingly challenging problem solving.[33]

Solving stoichiometry: Particle diagrams or algorithms? Stoichiometry is an example of a topic in which reform proposals have often advised change: moving away from teaching algorithms toward solving based on concepts described by particle-level diagrams. Cognitive studies suggest there is a right -- and wrong -- time for both.

Chemical reactions are the heart of chemistry. After learning fundamentals of atom conservation, bond breakage, and bond formation, learning to solve *simple* reaction calculations with simple particle counts by drawing particle diagrams is clearly essential in any introductory course.

But students who aspire to be chemists, medical professionals, and engineers are also expected to solve reaction calculations with complex data. In such cases, due to working memory limits, cognitive science is emphatic: To reliably solve complex problems, students must apply a memorized algorithm.

For a given topic, which algorithms should be taught? Whichever the instructor has found by research to most often result in right answers. Such algorithms will generally be incremental, highly-structured, easy to remember, relatively quick, widely applicable, have fundamental relationships at their core, and rely on previously well-memorized relationships to circumvent working memory overload.[4,25,34,56]

Particle-level diagrams for simple problems, but algorithms for complex, has traditionally been how stoichiometry was taught. What cognitive science has added is an explanation for why, for complex problems, an algorithmic approach is necessary.

Non-majors need implicit, not explicit, understanding. Non-experts (students) can learn to solve complex problems. In courses such as general chemistry, they do so. But cognitive studies have established that during problem-solving, the "non-expert" brain bases its decisions on what to do, and what to recall when, on implicit, intuitive, tacit, often unconscious conceptual understanding. In most human activities, the brain acts based on subconscious understanding of what to correctly do without explicitly being able to explain why.[4,25,28]

For example, even without schooling, children above age 3 nearly always correctly apply the complex rules for the morphology, syntax, and semantics when they speak their primary language. Yet even as adults, except for majors in linguistics, most of us can state very few of the rules that govern our speech.[14,28] Another example: Most science majors (and their instructors) can use math as a tool to solve scientific problems, but rarely need to recite or explain the rules of mathematics during problem solving. Doing so would tend to cause confusion, due to "timing out" losses from working memory.

By graduation, we want chemistry majors to be able to explicitly explain why and how chemistry works. However, the vast majority of students in college general chemistry aspire to be science and engineering but not chemistry majors. For this substantial majority, the additional time required to learn to explain explicit understanding must be weighed against the time this would take away from practice solving varied problems. The brain requires practice to gain the implicit understanding needed to recall effective algorithms.

Guided inquiry? *After* learning fundamentals. Cognitive scientist Daniel Schwartz and colleagues have documented that guided inquiry activities which "take a few minutes rather than days" can "set the stage" for learning a new topic.[57] But scientific studies also find that for longer guided inquiry, as cognitive scientist Barak Rosenshine summarizes, "The most effective teachers … went to hands-on activities, but always after, not before, the basic material was learned."[58]

Cognitive studies tell us that students need to learn chemistry in part by initially memorizing facts and procedures. Cognitive experts also acknowledge the need "to find tasks that provide practice while at the same time sustaining interest."[59] Many of the activities in recent reform curricula are quite interesting, and science says can be effective in building frameworks—if conducted "always after" fundamentals are quickly recallable.

WORK-AROUNDS THAT WORK

In disciplines such as chemistry, what additional strategies do cognitive experts recommend?

To limit memorization, instructors should identify fundamentals.   Wiring the brain requires biochemical resources. Because the quantity of LTM wiring that can be grown

physiologically each day is limited, a key question for students is "what is most important to overlearn?" Cognitive experts recommend instructors both identify, and then ask students to overlearn, "core skills and knowledge that will be used again and again."[33]

Reference textbooks cover content in great detail. If a topic introduction by an instructor identifies knowledge essential to construct a basic conceptual framework for the topic, subsequent learning should progress more quickly. Furst summarizes, "Time is better spent at teaching the basics then trying to teach the new without it."[18]

Overlearn vocabulary early. For students in introductory courses, pico-, phosphate, P, *P*, Pb, *pH, pKa,* and kPa may be an unfamiliar foreign language. Until fundamental definitions can be activated during problem solving, additional wiring of chunks will be limited at best.

The foundation for new learning is what the student already knows.[18,24,60]

Willingham advises, "Knowledge is not only cumulative, it grows exponentially. Those with a rich base of factual knowledge find it easier to learn more—the rich get richer."[24] In learning, exponential growth is desirable -- and benefits from starting early.

Gradually construct meaning. After elements have been made initially recallable, during problem solving, more slots in working memory tend to be available for context cues. When processing includes contextual cues, deeper understanding of the meaning of elements is wired. More meaning helps the brain judge which facts and procedures to recall for different types of problems.[21,27]

Willingham suggests that instructors "[E]xplain to students that automaticity in facts is important because it frees their minds to think about concepts."[34]

Before **problem-solving begins, make fundamentals initially recallable.** If students begin to solve problems before fundamentals are recallable, working memory tends to overload. Successful problem solving, needed to promote LTM storage and wiring, is more likely if fundamentals are made initially recallable first.

Pre-requisites must be overlearned. If pre-requisite fundamentals are not recallable, "refreshing memory" should be practiced first.[18] The primary prerequisite for general chemistry is quick recall of 10-12 years of arithmetic and algebra. Without this automaticity, working memory tends to overload or time out during scientific calculations. In addition, if students can follow an explanation of a quantitative concept such as kinetic energy using mental math, slots in working memory are more likely to be available to process conceptual linkages.[34]

Unfortunately, science's discovery of the importance of automaticity has been slow to disseminate in both math and the sciences. As a result, for many current U.S. students, a part of K-12 schooling has included years in curricula that de-emphasized mental math.[37]

To improve general chemistry success, review to achieve computational automaticity may be advised.[8,61-65]

ADDITIONAL STRATEGIES FOR LEARNING

Solving problems in chemistry requires much more than initial memorization. Additional reading is suggested on "interleaved" problem sets,[53] elaboration,[49] dual coding,[43] and the use of demonstrations and inquiry to build frameworks.[42,58] But to *begin* learning a new topic, initial recall of fundamentals must be achieved, and spaced overlearning of those fundamentals should follow. As instructors, can we apply these scientific discoveries to help students speed and retain their learning?

EXPERIMENTS FOR EDUCATORS

Below are some ideas for formal or informal experiments in the application of cognitive science in courses prior to and including college general chemistry. The intent is that modifications of instructional designs be gradual, tested, adapted, and tweaked. Every class has unique students, goals, and resources.

Experiment with student preparation for lecture. For each new topic, some new components are complex, context dependent, and conditional. They benefit from written, graphic, and auditory explanation. But some relationships, such as vocabulary definitions and key equations, are short, precise, and the same across contexts. These can be learned before a first-day lecture if definitions are posted and a first-day quiz is set.

Might learning well-defined fundamentals before lecture result in improved learning? Experiments exploring options might include:

- A day or two before the start of a new topic, in a flashcard or table format, supply 12-20 new relationships essential for solving topic problems. Announce a 5-minute quiz on their content on topic day one.

- As an alternative, base the first-day quiz on a one-page posted explanation of "basics with some context," asking students to design their own flashcards from the content.

- To motivate on-time preparation, a quiz must count to some extent, but once the value is established, it may suffice to mix "going over" with grading the quiz.

- To promote spaced overlearning, test a rule that on "preparation for lecture" quizzes, 50% of questions will be from previously assigned "fundamentals to overlearn."

Activate prior learning. To begin mid-topic lectures, ask students to solve a problem with content from a previous class but needed today.[58] Neuron activation from a prior problem lingers and assists with lecture comprehension.[18]

Contrive "mental math" problems. Consider asking students to "estimate, then calculate." Then, after practice in mental math, design some chapter tests to be "no calculator" (see references *7* and *65*). If students cannot estimate to check a calculator answer, can we say they understand chemistry?

When demonstrating or assigning calculations, contriving "whole number" data that can be solved by mental math leaves slots open for context cues.[34]

Help students learn to study. Consider assigning the brief article at reference *64* describing how students can help themselves learn in higher education. If quiz questions on the article are promised, attention to content may be enhanced.

Find the best algorithms. Memorized algorithms are required for complex problems, but often many algorithms work. Which work best? The question merits research.

Address prerequisite mathematics. Faculty in both Texas and Minnesota have posted short, editable quizzes on the automaticity in mathematics needed for general chemistry (see references *7* and *62*). Given at the start of a course, these assessments may identify topics for which "refreshing of memory" is advised. Also found may be students who may benefit from 1-2 credits of "math for the sciences" prior to or concurrent with chemistry.

Measure your progress. Measurement of results requires comparison to a widely-accepted standard -- such as an ACS Examination with national norms. Quantification of increased departmental success in gateway courses for science and engineering majors may assist department leaders who work to increase resources for instruction.

Explore additional perspectives. For more summaries of the science of learning, see references *58* (at page 19), *60, 18*, and *42*. For additional detail, see references *35, 36,* and *67*.

CONCLUSION

What science has found about memorization may be disappointing, but as scientists, we have no choice but to respect the domain expertise of scientists who study how the brain works. When young people come to us for help in learning, we are obligated to follow scientific best practices.

Teaching science's strategies of chunking, automaticity, and algorithms can help students work around the working memory bottleneck. Fundamentals can be mastered by spaced overlearning. Do such strategies support a "drill and practice" approach to learning chemistry? In part they do, and drill and practice was a part of what worked for past generations who learned chemistry. But in part these new strategies are not the same.

Cognitive science suggests that in a new topic, if instructors identify fundamental facts and procedures, and ask students to practice recall *before* starting to solve problems, needed chunks will wire more quickly.

If instructors assign practice problems in a variety of contexts, and draw attention to the meaning of problem solutions, frameworks will wire more quickly. Timed appropriately, demonstrations and inquiry problems can move distinctive cues into memory. By determining and helping students learn the most efficient algorithms, instructors can promote increased student success in gateway courses to science majors.

Cognitive science's verification of what works, based on working memory's limitations and strengths, opens extensive opportunities for formal and informal research by chemistry educators. Understanding and applying new science, we can design more effective instruction.

Cognitive science is inherently our science: the science of learning, central science in the work we do.

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NOTES

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