

Taking a Scientific Approach to Science Education, Part I—Research

Developing expertise requires intense practice that includes doing challenging and relevant tasks, followed by feedback and reflection on one's performance

Carl Wieman and Sarah Gilbert

During the past few decades, major advances in the fields of cognitive psychology, brain research, and discipline-based education research in college science classrooms are providing guiding principles for how to achieve learning of complex knowledge and skills such as science. In part I, we describe the nature of expertise and how it is learned, primarily based on the findings of cognitive psychology. We also give examples of studies in undergraduate science classrooms and the resulting student outcomes compared with those from traditional lecture instruction.

In the second feature of this two-part series, we will discuss the challenges and opportunities for making these teaching methods standard practice in undergraduate science classrooms and the results of a large-scale successful experiment in doing so.

The Nature and Learning of Expertise

Learning to think about and use science more like a scientist who is already working in the discipline is a primary educational goal for most undergraduate science courses. But exactly what is meant by “thinking like a scientist”—in other words, what is scientific expertise? Cognitive psychologists have extensively studied expertise across a variety of disciplines, including history, science, and chess. They find three components that are common to all fields:

- large amounts of specialized knowledge
- a specific mental organizational framework, unique to the field of expertise
- the ability to monitor one's own thinking and learning in the field of expertise

Although the first component is no surprise, knowing lots of information is not useful if a

person cannot quickly recognize how that information can solve a particular problem. Experts organize information in unique discipline-specific frameworks for efficient and accurate retrieval and application. This practice entails grouping information according to certain complex patterns and relationships. Much of what are called scientific concepts are the way that experts in a field of science link lots of information within a single category, thus allowing them to decide quickly where that information is relevant.

The third general characteristic of expertise is the ability to monitor one's own thinking. When working on a problem, a scientist is regularly asking: Is this approach working? And do I really understand this? Experts have the resources to answer those questions and modify what they are doing accordingly.

Research indicates that everyone requires many thousands of hours of intense practice to reach a high level of expertise. This requirement to spend so much time in developing expertise is set by biology. The brain changes through this intense practice, and is rewired to build these expert capabilities. Much as a muscle develops in

SUMMARY

- To acquire expertise, one must develop a large body of specialized knowledge, a specific framework for that knowledge, and a capacity to monitor his or her own thinking about that field.
- Teachers need to have mastery of a field of expertise and convey the importance and excitement of that field.
- Many active learning approaches achieve greater learning than conventional lectures.
- Preliminary findings indicate that it is better to delay the use of jargon in classes until after students are introduced to the relevant concepts.

response to prolonged intense exercise, the brain responds to intense “mental exercise.”

In addition to identifying generic components of expertise, cognitive psychology research also identified a common process required for developing expertise, called deliberate practice. It involves many hours of intense practice, but that practice must have very specific characteristics. It must involve tasks that are difficult for learners, requiring their full focus and effort to achieve, but that are still attainable. The tasks must also explicitly practice the specific components of expertise to be learned. Finally, there must be timely and specific feedback, typically from a coach or teacher, on how well a learner has done and how to improve, and then reflection by the learner on how to use that guidance.

Components of Scientific Expertise

A few examples of specific components of expertise in any area of science include:

- recognizing and using concepts and mental models and developing sophisticated selection criteria for deciding when specific models are applicable
- recognizing relevant and irrelevant information for solving a problem
- knowing and applying a set of criteria for evaluating if a result or conclusion makes sense

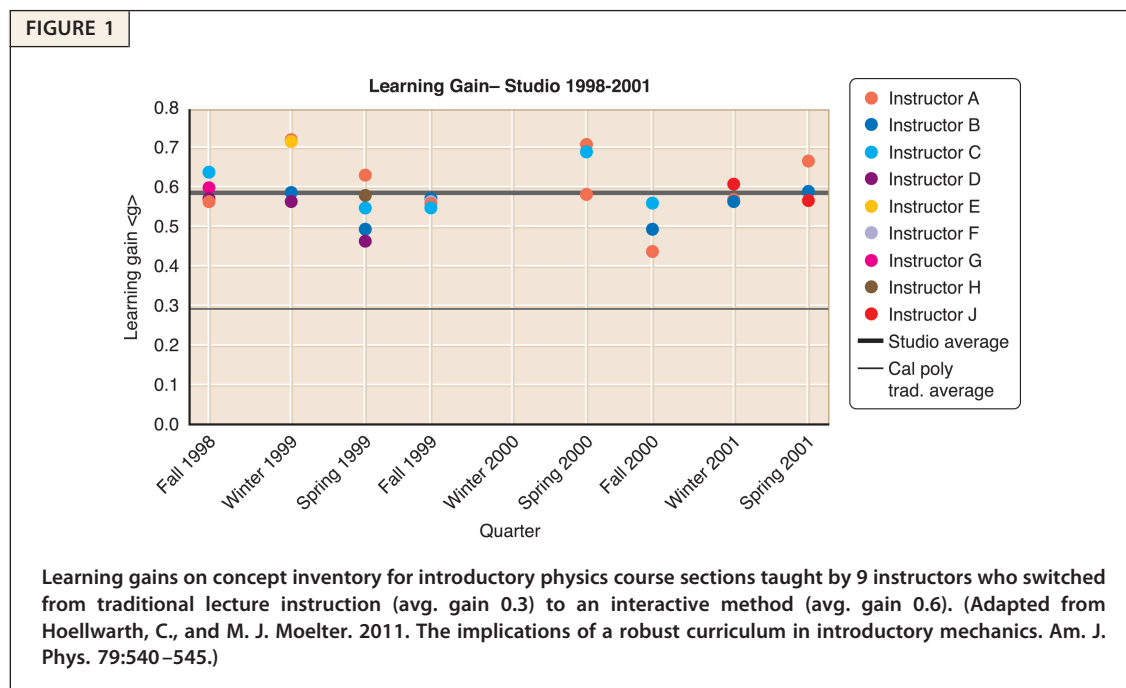
- moving fluently among specialized representations such as graphs, equations, and specialized diagrams.

We selected these particular examples because they are seldom practiced with feedback in typical undergraduate science courses.

A highly effective teacher maximizes the amount and effectiveness of deliberate practice by students. This role requires them to have substantially more content expertise than does traditional teaching by lecture. Teachers must have deep expertise in their respective disciplines to design suitable tasks that provide authentic practice of expert skills for their students at the appropriate level of challenge. The teachers also must have substantial content expertise to provide specific feedback on how well the students are performing those tasks and how they can improve performance. Finally, since this practice is inherently hard work, it requires motivation. An expert in the subject is uniquely positioned to help provide that motivation by conveying the importance and excitement of the subject.

Examples of Studies on Learning in Undergraduate Science Courses

Here are several examples of studies on learning in science courses. The first comes from a study



conducted by Chance Hoellwarth and Matthew Moelter in an introductory physics course at California Polytechnic State University. Their study involved many different instructors of physics across many sections and looked at the amount of learning before and after these same instructors changed their teaching methods.

Hoellwarth and Moelter used a validated and widely used concept inventory test to measure student learning gains on core concepts covered by the course. The learning gain is a measure of the fractional amount a student improves between their pre-course score and post-course score on the test, with a gain of 1 meaning a perfect score on the post-test. Hoellwarth and Moelter collected such data for students for a number of years while classes were taught using traditional lecture instruction (Fig. 1, the Cal Poly Trad. Avg. line). The average learning gain was a bit less than 0.3, which is typical for a well-taught lecture course on introductory physics.

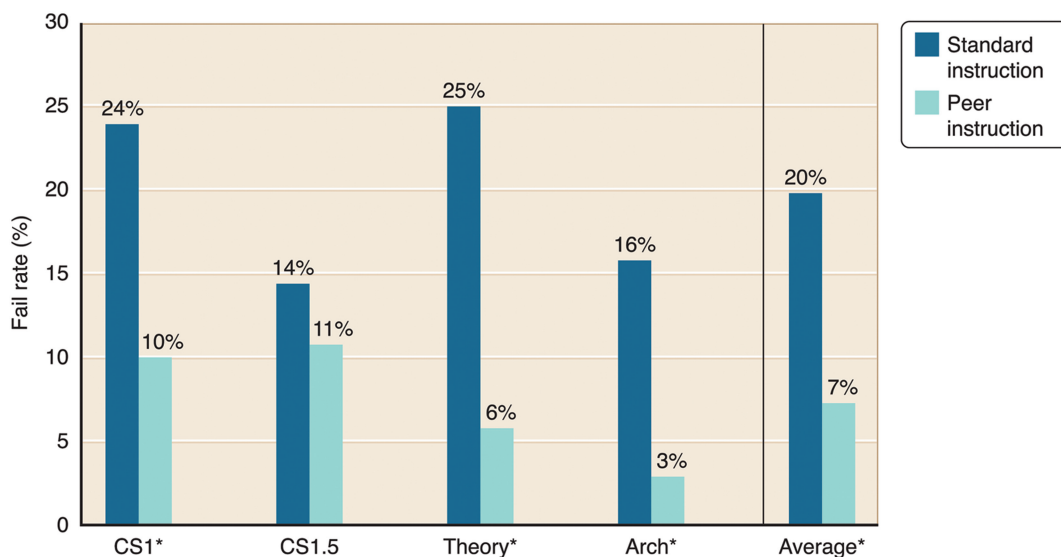
Next, all the instructors switched to a “studio” approach, in which the students worked in small groups to carry out a common set of carefully designed tasks, and the instructors served as facilitators/coaches. After this switch, the average learning gain doubled to 0.6 (Fig. 1). We want to

emphasize that this change occurred with the same set of instructors who changed the teaching methods that they were using, after which their students learned far more of the concepts being covered.

Our second example is from the work of Beth Simon and coauthors in Computer Science at University of California, San Diego. Simon spent a year working with us and learning about the active learning technique for teaching introductory physics called Peer Instruction. This approach involves regularly posing questions to students during classes, having them answer with clickers that record their responses, and then having them discuss the material in small groups before re-answering those questions.

Simon worked with six other instructors to introduce this method in four core courses in computer science. There was a dramatic decrease in the drop and failure rates across all four courses, with the overall average being about 1/3 of what it was previously (Fig. 2). This figure represents a very large number of students who, only because the instructors changed their teaching methods, are now successfully pursuing degrees.

FIGURE 2



Failure rates for 4 computer science courses when instructors used standard instruction vs. interactive Peer Instruction. (Adapted from Porter, L., C. Bailey-Lee, and B. Simon. 2013. Halving Fail Rates using Peer Instruction: A Study of Four Computer Science Courses. Proc. 44th ACM Technical Symposium on Computer Science Education (SIGCSE '13), p. 109–114.)

Those two studies, the first by Hoellwarth and Moelter and the second by Simon and her collaborators, looked at the final results of students taking full courses. However, a great deal of learning takes place outside classrooms while doing homework assignments and studying for exams, for example. This raises the research question, how much difference do these research-based teaching methods make in the learning that takes place only in the classroom, which is the main focus of most instructors' attentions?

This classroom component of learning was measured using two large sections (270 students each) of the introductory physics course taken by all engineering students at the University of British Columbia, by one of us (CW) and collaborators L. Deslauriers and E. Schelew. Before the experiment, the performances by students in two separate sections were carefully measured and seen to be nearly identical. Thus, within the small statistical uncertainties of such large classes, their scores on tests of conceptual mastery, on two midterm exams, attitudes about physics, attendance, and engagement in class were nearly identical.

One section was taught by a senior professor who taught this class many times with good student evaluations. Another, experimental section was taught for only one week by someone with a Ph.D. in physics who had limited teaching experience but was trained in the principles of learning and research-based teaching practices in the program that we ran. Both instructors agreed on the same set of learning objectives to be covered in the same amount of class time. The timing of our experiment was set so that students would be unlikely to do much studying outside class during the week that the experiment took place.

The instructor of the experimental section used a number of common features of research-based teaching. Students were assigned short, targeted readings before class and given a quiz on the reading. During class they were given questions to answer, where they would respond with clickers or by completing worksheets. This process involved each student in individual work and discussions with their neighbors, during which time the instructor would circulate through the room listening to those discussions. There was considerable instructor talking, but predominantly as follow-up discussion to the activity, not preceding it. So in this way, students were prac-

ticing scientific thinking and receiving feedback from their fellow students and an informed instructor.

After the week-long experiment, the students were given a pop quiz at the start of the following class, a quiz that the instructors jointly developed to probe the mastery of the learning objectives during the experiment. The difference in performance between the control and experimental sections is very large—an effect size of 2.5 standard deviations—and is reflected in the entire distribution moving up (Fig. 3). This result reflects what also is seen elsewhere, namely, these teaching methods are not just beneficial for a subgroup of students, they are much better for *all* students. This broad applicability is not surprising; the teaching methods are based on research on how the human brain learns. In this study, the average level of engagement of the students was also measured and, as one might expect, it was much higher (85%) in the experimental section than in the control section (45%). Many other studies show similar results, including many in biology, according to numerous reports in the journal *CBE-Life Sciences Education*.

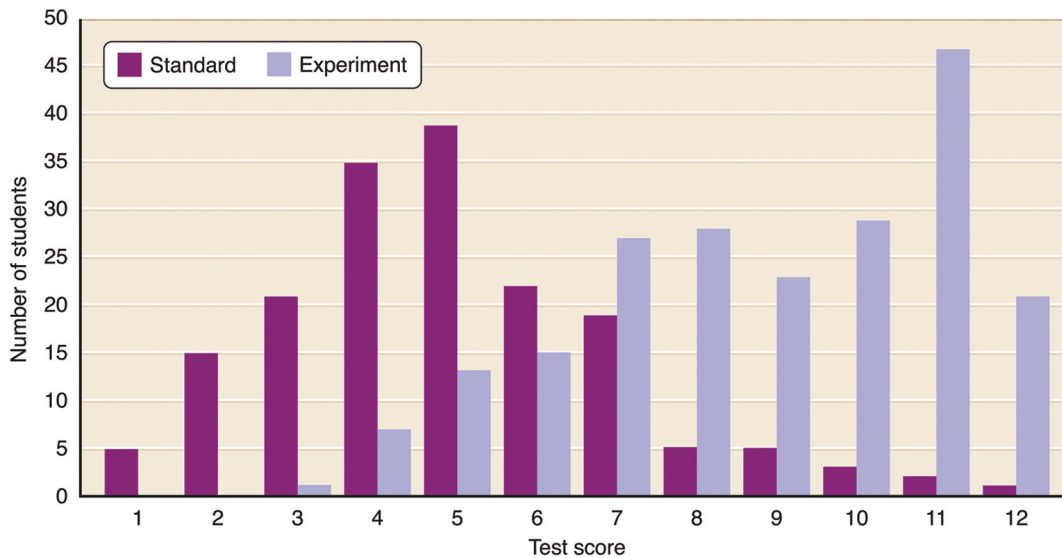
Impact of Jargon when Teaching Biology

We are involved in another study evaluating the impact of jargon on learning in biology. This work was inspired by cognitive psychology research studying the limits of the short-term working memory.

In simple terms, memory can be described as having two components. Long-term memory has enormous capacity and lasts for decades. The second component, short-term working memory, is what we use on short time scales, such as time spent in a class, to remember and process new information. In contrast to the long-term memory, the working memory has extremely limited capacity, around 5–7 new items for the typical person. As the working memory also processes information, it operates analogously to a PC with very little RAM. The more it is called up to remember and process, the less effectively it can function.

Many studies show that anything that increases demands on the working memory unnecessarily during a learning activity reduces learning. We, with Lisa McDonnell and Megan Barker, designed an experiment to test if reducing the amount of jargon introduced in a biology class

FIGURE 3



Test scores for students taught an introductory physics module using standard instruction vs. students taught using interactive engagement techniques. Random guessing would produce a score of 3. (Adapted from L. Deslauriers et al., *Science* 332:862–864, 2011.)

would improve learning of the biology concepts. Although the study is ongoing, preliminary results show large benefits from introducing relevant jargon only after students are introduced to the concepts.

These are just a few examples. As shown in a meta-analysis by Scott Freeman and coauthors, there is a vast literature of similar studies across the science and engineering disciplines, providing overwhelming evidence that interactive teaching approaches are much more effective than conventional lectures at achieving learning of complex subjects.

Carl Wieman holds a joint appointment as Professor of Physics and the Graduate School of Education at Stanford University, Stanford, Calif., and Sarah Gilbert is a senior advisor at the Carl Wieman Science Education Initiative, University of British Columbia, Vancouver, Canada. This feature is based in part on a talk given during the 2014 ASM Conference for Undergraduate Educators.

Suggested Reading

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