Educational Psychologist

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/hedp20

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To cite this article: Daniel L. Schwartz (31 Oct 2024): Achieving an adaptive learner, Educational Psychologist, DOI: 10.1080/00461520.2024.2397389

To link to this article: https://doi.org/10.1080/00461520.2024.2397389

Published online: 31 Oct 2024.

EDUCATIONAL PSYCHOLOGIST
https://doi.org/10.1080/00461520.2024.2397389

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APA DIVISION 15 CAREER ACHIEVEMENT ADDRESS

Achieving an adaptive learner

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ABSTRACT

This essay was invited upon the receipt of the American Psychological Association Division 15's Career Achievement Award for Distinguished Psychological Contributions to Education in 2021. I propose that modern education should prepare students to continue learning so they can adapt to changing times, circumstances, and knowledge bases. A key step in adaptation is recognizing that there is something new. I review evidence from three sets of previous studies that show traditional instruction succeeds in helping students complete routine tasks but falls well short of preparing students to learn from new information and adapt it to novel situations. I try to understand these results from three levels of analysis: The overarching goals of instruction; the psychological assumptions underlying the instruction; and the *in situ* demands and natural responses of classroom learners. Given these analyses, I motivate four instructional design principles that emphasize helping students innovate new ideas and solutions, which in turn, leads them to focus on new information and prepares them to adapt and learn from future situations.

Ideally, modern education could prepare students to continue learning so they can adapt to changing circumstances and knowledge bases. Can we educate people to be more adaptive? There are many different approaches one might take to achieving an adaptive learner. These include offering strategies and attitudes, while teaching cognitive flexibility and creativity. These approaches, which have many merits, are knowledge indifferent. They do not address the starting point of adaptation; namely, knowing that there is something new. If people cannot pick up that there is something new, they cannot adapt. Here, I consider the effects of knowledge preparation on people's abilities to pick up new information and adapt.

I review three lines of research conducted approximately seven years apart that suggest traditional forms of instruction may be insufficient for achieving an adaptive learner. The traditional instruction produced positive outcomes on standard measures of efficient recall and procedural execution. However, when measured by adaptive outcomes, the instruction had little benefit. Originally, I entered the studies with the assumption that the "experimental" instructional treatments would outperform the control conditions of traditional instruction. I did not anticipate that the traditional instruction would be starkly ineffective at achieving adaptive outcomes.

This essay attempts to explain why traditional instruction fails to achieve adaptive learners. I work from three levels of explanation. The first level considers two broad trajectories of learning associated with routine and adaptive outcomes—efficiency and innovation. I propose that an over-emphasis on the efficiency dimension, a common characteristic of traditional instruction, may trap students on a trajectory toward non-adaptive outcomes. For the second level of analysis, I point to an over-arching cognitive assumption behind many theories of instruction. The prevailing assumption is that learning comprises going beyond the information given, for example, through elaboration or verbal explanation. Borrowing from theories of perceptual learning, I motivate the challenge of helping people to see the information in the first place, which I call the *challenge of information pickup*. Adaptation can only begin when people discern new information worthy of a response. Finally, after reviewing the three sets of studies, I analyze classroom task demands and natural psychological forces to explain why students of traditional instruction do well on routine tasks but not adaptive ones. These three levels of analysis set the stage for describing four principles that guided the design of the "experimental" conditions in the studies. Together, the principles may offer a prescription for how to avoid the risks of traditional instruction while also creating conditions for achieving an adaptive learner.

This invited article is on occasion of receiving the Lifetime Achievement Award from the Educational Psychology branch of the American Psychological Association. It is a great honor for which I am appreciative and surprised. The topic of this article differs from the award speech, which discussed embodiment and learning. However, it maintains some of the style of a talk with everyday examples.

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Differentiating two courses of learning

All learning creates changes to the brain. Learning, however, is not a single thing. Humans house many different types of learning that include reinforcement, imitation, perceptual differentiation, verbal learning, motor learning and more (see Schwartz, et al., 2016). Just as the immune system houses many different processes for handling recurrent problems and adapting to novel ones, the brain has multiple processes for learning and using information. As I discuss below, the different learning processes can be orchestrated to achieve two trajectories of learning.

Trajectories toward adaptive and routine expertise

One trajectory is associated with increases in efficiency, and the other is associated with innovation. The differentiation of efficiency and innovation was captured by March (1991), who identified two modes of organizational learning, which he termed, *exploitation* and *exploration*. Exploitation optimizes known efficiencies, through processes of "refinement, choice, production, efficiency, selection, implementation and execution" (p. 71). Exploration pursues new alternatives. It is characterized by "search, variation, risk-taking, experimentation, play, flexibility, discovery and innovation" (p. 71).

Hatano and Inagaki (1986), looking at individuals rather than organizations, also proposed two paths for learning. One path is characterized by low contextual variation, a strong reward function, and an emphasis on expediency. The second path invites contextual variation, playfulness, and a culture that pulls for explanation. Hatano and Inagaki proposed that the endpoints of these pathways are routine and adaptive expertise, respectively.

Routine does not mean pedestrian. It means routinized or highly efficient. "[R]outine experts are outstanding in terms of speed, accuracy, and automaticity of performance, but lack flexibility and adaptability to new problems" (Hatano & Inagaki, 1986, p. 31). Their leading example was abacus grand masters. The masters handled prodigious numerical sums by mentally simulating an abacus. The masters were surely experts, yet they only performed under highly stable conditions and their abilities did not generalize beyond tasks involving digit manipulation. Hence, they were called routine experts. Using March's language, the abacus masters exploited and refined their abilities at mental calculation to an astonishing degree.

Cognitive research on learning has made great strides in understanding how to increase efficiency. The field has benefited from investigating behaviors that are objectively right or wrong, as in remembering the correct word, giving an accurate answer, or executing a skilled behavior. Bryan and Harter's (1899) ground-breaking studies of teletype operators noted a learning curve that is now called the *power law of learning*. They tracked changes in the efficiency with which the operators could send and receive teletype messages. The operators showed steep gains in the early months. Over time, the gains became asymptotic as the operators slowly squeezed out the remaining inefficiencies. Since then, considerable research has examined the steps by which complex skills, such as driving a car, move from controlled processing to automaticity through a sequence of chunking discrete steps into highly efficient bundles (Anderson, 1982). As another instance of efficiency research, the voluminous literature on memory has identified the importance of elaboration and retrieval practice on improving the accuracy of recall. As one last instance, Ericsson et al. (1993) documented the importance of deliberate and effortful practice coupled with copious feedback for accelerating the acquisition of expertise. It may be fair to say that if people are willing to put in the time and effort, cognitive psychology has effective prescriptions for how to make them faster, more accurate, and less variable.

In contrast to routine expertise, Hatano and Inagaki (1986) proposed that adaptive experts have a deep understanding of why skills work and their conditions of application. This enables them to consider alternatives depending on a changing context, and "invent new procedures and/or make new predictions" (p. 28). An academic example of adaptive expertise comes from Wineburg (1991). History professors, who were not experts in American history, received historical documents regarding a battle during the American Revolution. Their task was to decide which of several paintings was the most accurate. The professors applied a set of disciplinary heuristics, such as searching for corroborating information across documents, which enabled them to adapt to the new context of American History. They were able to see reliable patterns across the descriptions and paintings. High school students, given the same task, "saw only a collection of details" (p. 83). An instance of the need for adaptive expertise comes from the medical field (e.g., Mylopoulos et al., 2018). Doctors must master and efficiently deploy a massive body of knowledge, while also adapting to discrepant symptoms and emerging treatments.

Compared to research on efficiency, there is less evidence on the characteristics and sequences of learning that achieve adaptive expertise. One might reasonably speculate that adaptive experts invite variation; they try to explain why; they tolerate ambiguity and hold hypotheses lightly; they are willing to be wrong (for a while); they seek feedback and new information; and, they have a strong body of efficient knowledge to support the generation of useful adaptations.

One relevant line of research examines content-agnostic strategies for enhancing the generation of new ideas (e.g., Dow et al., 2010; Ionescu, 2012). *Design thinking* includes a variety of strategies to avoid being trapped by old ways of thinking (Razzouk & Shute, 2012), and inquiry training emphasizes systematic investigation to aid in the discovery of empirical patterns and underlying causes (de Jong, 2019). Another useful line of research involves knowledge-dependent pathways for handling novelty, such as analogy generation (e.g., Gentner et al., 2003). People are more likely to use their knowledge to handle novel situations if they identify the deep similarities across prior instances (Gick & Holyoak, 1983).

In this article, I highlight research from perceptual learning, which asks how people can learn to see what they could not before. Sometimes, the need for adaptation can be manifest, as in the case of a worldwide pandemic. But it is often more subtle. People may continue their routines without ever noticing a productive opportunity to adapt. A favorite example involves American tourists in Italy, who become annoyed by the slowness of dinner service rather than noticing how Italians enjoy their evening meal.

A framework of trajectories toward expertise

With David Sears and my brilliant colleague John Bransford (see Hmelo-Silver et al., 2023), we proposed a simple framework that combines the insights of March with Hatano and Inagaki (Schwartz et al., 2005). In Figure 1, movement along the horizontal dimension reflects an increase in efficiency. For example, as children receive practice solving problems such as $4+4+4=12$, they improve their speed and accuracy. This behavioral change is correlated with the transfer of computation in the brain from controlled processing in the pre-frontal regions to the interparietal sulcus and specialized processing (Rivera et al., 2005). Their practice moves them along the horizontal dimension toward routine expertise, which we located in the lower-right corner of Figure 1. Routine expertise is the horizon of efficiency.

The vertical dimension reflects cumulative experiences at innovating ideas and rendering solutions. For example, students may try to invent a new way to solve a novel problem, such as finding 1/3 of 12 pieces. Efforts toward innovation are solution-oriented explorations.

People who reside in the upper-left corner of Figure 1 are strong on innovation experiences but weak on content knowledge. It will be hard for them to make effective adaptations because they do not know relevant procedures and contextual constraints that make a solution successful. Creativity is often operationalized as the production of novel and appropriate ideas (Oppezzo & Schwartz, 2014). When ideating about the possible uses of a brick, taking a brick to clean teeth would be novel but not appropriate. People in the upper-left corner have strategies for producing novel ideas, but their lack of strong domain knowledge limits the appropriateness of their ideas. Ideally, they pair their knowledge-free strategies with a partner who is high on efficient domain knowledge.

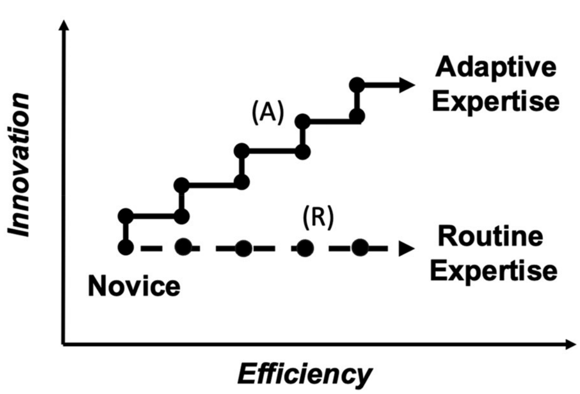

Figure 1. A framework for considering experiences that drive trajectories toward routine and adaptive expertise. Trajectory (R) proposes that students who begin instruction on an efficiency trajectory will have difficulty escaping the pull toward routine expertise. Trajectory (A) proposes that the path to adaptive expertise can begin with innovation efforts followed by the delivery and practice of efficient solutions and theories (Adapted from Schwartz et al., 2005).

A trajectory to adaptive expertise depends on balancing efficiency and innovation. Children may not be able to solve the novel problem of finding 1/3 of 12 pieces if they do not already know that $4+4+4=12$. March (1991) provides a nice summary of the perils of pursuing a trajectory that only moves along one dimension:

> Adaptive systems that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining many of its benefits. They exhibit too many undeveloped new ideas and too little distinctive competence. Conversely, systems that engage in exploitation to the exclusion of exploration are likely to find themselves trapped in suboptimal stable equilibria. As a result, maintaining an appropriate balance between exploration and exploitation is a primary factor in system survival and prosperity. (p.71)

The dashed horizontal line (R) reflects my proposal that instruction that begins on the efficiency path may make it difficult for students to take the inflection toward adaptive expertise. The traditional forms of instruction that I describe in the following studies implicitly emphasize the efficient delivery and recapitulation of information. They put students on a trajectory toward routine expertise such that the students miss opportunities to adapt.

The stylized staircase trajectory (A) from novice to adaptive expertise reflects a positive proposal for how to move students toward adaptive expertise. To avoid the pull toward efficiency, students can engage in activities that promote innovation. If done well, these activities can help students discern and induce what is new, which prepares them to adapt. Moreover, the innovation-first experiences can prepare students to understand solutions and theories more deeply, because they can see the key features of the problem being solved. Students on trajectory A still need to learn and practice efficient solutions and theories. However, unlike students on trajectory R, they will be able to use those theories and solutions to handle novel situations. The Innovation -> Efficiency staircase is consistent with the problem solving before instruction framework by Loibl et al., (2017). As they point out, not any problem solving will do, which I return to when describing four principles for creating effective innovation experiences.

Assumptions about learning and the information pickup challenge

My second level analysis considers the broad psychological theories that undergird instructional design. Throughout my career I have kept a folder of compelling articles. One of my favorites is *Perceptual Learning: Differentiation or Enrichment* (Gibson & Gibson, 1955). Their question was how people learn to perceive what they could not before. An expert archeologist can see details in the soil that a novice cannot (Goodwin, 1994). A wine sommelier can discern subtle flavors whereas a novice might notice red versus white (Solomon, 1997). Years after my initial reading, I realized the Gibson article is relevant to an assumption in most contemporary instructional models. It is also highly relevant to a fundamental challenge to being adaptive—perceiving new information.

Their article begins by noting that two competing intellectual traditions share a fundamental assumption. The Gibsons proposed that both behaviorism and cognitivism were *enrichment theories*. Both traditions explained perceptual learning as the result of associations that enrich sensory stimulation (Sensory nerves capture physical energy, perception detects meaningful structure in sensation). For behaviorism, the association to the sensory stimulus was a reinforcement signal. Without a reinforcement such as a reward, people would not respond to sensory information. For cognitivism, the enrichment was the attachment of meaning, perhaps from a schema or the memory of prior experiences. The Gibsons then proposed a non-enrichment alternative they called *specificity theory*. People learn to perceive by detecting or "picking up" more of the information structure already in the world. They ironically noted that for enrichment theories, perceptual learning involves moving further away from the sensory world through the accumulation of associations. In contrast, by specificity theory, learning involves getting closer to the information present in the world.

The Gibsons provided a simple experiment using a scribbled figure of loops to show that learning involved making finer discriminations of the information structure in the stimulus. Over time, people started to notice the number of loops and the compression of the ovals in the scribble. The participants came to perceive distinctive structures that differentiated the targeted scribble from other figures without any reinforcements or elaborations.

The Gibsons' analysis is highly relevant to the trajectories toward routine and adaptive expertise. A routine expert does not need to perceive new information, because they work in familiar situations. To be on a trajectory toward adaptive expertise, people need to be prepared to perceive the new information that comes with new situations and ideas.

Revisiting an instructional debate

Among instructional theories, there has been a provocative debate between constructivist and non-constructivist advocates (see Tobias & Duffy, 2009). These two traditions share an assumption that underestimates one challenge of the trajectory to adaptive expertise—picking up new information. Instead, these theories emphasize *going beyond the information given* (Bruner, 1973), or in the Gibsons' terms, enriching the stimulus.

The line between the two approaches is not perfectly defined (Taber, 2010). As a coarse parsing, it seems that the family of non-constructivist teaching approaches might include explicit instruction that tells or shows students what to do and think. Whereas constructivist instruction might include activities through which students generate new-to-them knowledge. As parodies, one might imagine a dark auditorium of college students memorizing a 50-minute physics lecture versus undergraduates sent to a lab to work in groups to rediscover theories of physics that took centuries to work out. Neither extreme seems ideal.

The debate has remained unresolved for decades with competing meta- and rational analyses (e.g., Chi & Wylie, 2014; de Jong, 2019; Freeman et al., 2014; Hattie & Donoghue, 2016; Hmelo-Silver et al., 2007; Schuster et al., 2018; Zhang et al., 2022.) One explanation for the lack of convergence is the sheer number of ways to execute the two approaches. On the non-constructivist side, one might have students read a passage, listen to a lecture, follow a worked example, imitate a behavior, be rewarded for executing well, and more. On the constructivist side, students might engage in open-ended problems, scientific inquiry with simulations, making artifacts, project-based learning and more. The combinatoric explosion of the different tasks and psychological processes among all these forms of instruction is currently intractably large for exhaustive comparison (Koedinger et al., 2013).

These otherwise competing approaches nevertheless share a deep assumption that influences their instructional designs. Learning comprises going beyond the information given. For example, the worked example literature, which favors explicit instruction, argues that discovery activities will exceed limits on working memory (Paas et al., 2003). It is better to provide students with strong guidance to keep the information within the capacity limits of working memory. This way students can associate the steps with one another and their prior knowledge. The associations are an instance of enriching the stimulus. On the constructivist side of the debate, de Jong (2019), defines *engaged learning* and directly states, "Central to this definition is that students go beyond the information that is offered to them." (p.154).

Students do need to go beyond the given information, which is a reason for the common assumption. Chi et al. (1994) showed that a popular textbook chapter on the heart only stated a fraction of the relations among heart components. The passage would have to have been inordinately long to set forth all the connections. They proposed that self-explanation was an important strategy for going beyond the text information to develop a mental model of the heart.

As the Gibsons argued, going beyond the information given is not the only type of learning. People can learn by discerning new information (e.g., Goldstone et al., 2010; Kellman et al., 2010). Discerning new information is critical for adaptation. If there is new information, people need to detect it to have an adaptive response. Presumably, constructivist and non-constructivist approaches to instruction would agree that students need to gain new information, before they can enrich it. Yet, with an emphasis on going beyond the information, exacerbated by a press toward efficient performance, instruction can overlook the challenge of helping learners see new information in the first place. For example, Zhang et al. (2022) take it for granted that people will notice novel information. They state "Humans have evolved to automatically obtain novel information either by problem solving or from other people. It is far more efficient to obtain information from others than to generate it oneself during problem-solving." (p.18). While there is a novelty effect (Tulving & Kroll, 1995), it only takes hold if people recognize there is novel information, which they often do not. As I demonstrate below, traditional instruction does not always do enough to help students learn to perceive new information.

The challenge of information pickup

One possible reason most traditional models of instruction neglect challenges in discerning information is that it seems non-problematic. For experts, relevant information is readily discerned. It can be hard to imagine that other people cannot see it. Afterall, it is in plain view. Nathan and Petrosino (2003) called this *the expert blind spot*. The purpose of this section is to motivate the *challenge of information pickup* and convince the reader that it could be a real problem for learners.

The challenge of information pickup largely occurs because of an over-abundance of information. Even simple situations contain a large amount of information. If one looks at a circle, there will be information about its size, color, internal filling, border, location, lighting, time of day, and so on. It can be hard to know what is relevant until there is a clear purpose for its use. Consequently, people may encode the most general category possible—a circle. As a demonstration, Nickerson and Adams (1979) created 15 variations of a U.S. penny. For example, they faced Abraham Lincoln to the left or the right. Despite having handled thousands of pennies very few people *were* able to discern which variation was the true penny. People had encoded the features of a penny to the least specific level they needed to discriminate a penny from a nickel, a dime, and so forth. The more specific information was unnecessary and unheeded.

To handle information over-abundance, people have selective attention. Selective attention leads people to see what they are looking for. For instance, given a new toy with many interactive features, infants will confine their interactions to what their parents demonstrate, whereas infants who are not shown anything will explore and find more features of the toy (Bonawitz, et al., 2011). A fabulous example involves adults who watched a video of people tossing a ball to one another as the people moved about a room (Simons & Chabris, 1999). The participants' task was to count the total number of tosses. During the video, an actor in a full-size gorilla suit enters the room, walks among the adults, and faces the camera to thump its chest. Most participants never saw the gorilla, because they were focused on what they were looking for—the number of times the ball changed hands. The great constructivist, Piaget (1954), described how children may fail to accommodate to new information, because they assimilate the information to their existing schemas. Sometimes, people miss the information altogether.

A related challenge is that novel situations are rarely so chaotic that people do not have an interpretation. People's ability to make sense of any situation can shut down the search for novel information (see Alibali et al., 2018). When children first see a rainbow, the new information is obvious, and they see it. The problem occurs when there are deeper structures of information that people may not immediately perceive. For example, the colors have a specific ordering. Blair (2009) conducted a study with children who had to compute distances for launching a ball and then they saw how far off the ball landed from the target. The children exhibited a stable progression. Initially, the children simply noticed whether their computation was right or wrong. Then they noticed whether their computation was to the left or right of the target. Next, they noticed if their computations were near or far from the target. Finally, they noticed the exact direction and distance their answer was from the target, which finally allowed them to design a precise computation to solve the problems. This progression fits Gibson and Gibson's (1955) suggestion "… that the stimulation is complex, not simple, and that the observer continues to discover higher-order variables of stimulation in it" (p. 40).

Measuring adaptation to new information

Current measurement systems are predominantly designed to measure progress toward efficient outcomes. They evaluate people's abilities to solve retrieval, procedural, or conceptual problems in a sequestered format (Bransford & Schwartz, 1999). Students do not have access to any new information that would enable them to learn and adapt during a test. A review of studies of professional experts showed that many studies measured experts' abilities to handle novel problems, which is an important talent for adaptation (Carbonell et al., 2014). However, the measures had no way to capture the experts' abilities to pick up new information, a key component of adaptiveness.

Dynamic assessments provide an alternative form of measurement that introduces new information as part of the overall assessment. Dynamic assessments can detect whether students are on a trajectory to adaptive expertise, because they can evaluate whether students can pick up the new information. Feuerstein (1979) introduced the idea of dynamic assessment in his work on intellectual disabilities. Rather than simply using an IQ test to measure children's functioning, Feuerstein taught the children how to solve the kinds of problems that appear on an IQ test. Afterwards, he gave an IQ test to see how well they learned what he had taught them. He found the dynamic assessment to be more diagnostic of the educability of the children compared to just giving the IQ test straight away. He turned a measure of intellectual functioning into a measure of abilities to learn, which is closer to the aims of education.

A dynamic assessment can be conceptualized as having two stages. In stage one, there is the delivery of new information from which students can learn. The three sets of studies described in the next section use stage one as a way to compare two instructional approaches. Students complete their initial learning in one instructional treatment or the other. Afterwards, they enter the first stage of the dynamic assessment. All the students are exposed to the same new information that is relevant to, but goes beyond, their original instruction. Did the initial instructional conditions differentially prepare the students to pick up the new information?

Stage two of the dynamic assessment measures whether students use what they may have learned from stage one. In the following studies, there are two types of measures in the second stage. One form measured student progress on the efficiency dimension. Could the students solve problems that were similar to the forms of instruction and problems they had already received? For example, could they compute an answer or recall a fact? The second type measured progress along the adaptive trajectory. These were measures of spontaneous transfer, because they did not provide overt cues that students' prior learning could be adapted to the new situation. For example, could students make accurate predictions about a novel situation they had never encountered before, but contained new information that was relevant to what they learned in the first stage of the dynamic assessment?

Combined, the two stages of the dynamic assessment can be used to create a double measure of adaptiveness: Do students pick up new information to learn, and do they use that information to help further discern what is important in a new situation?

The effects of instruction on efficient and adaptive outcomes

The studies in this section evaluated ways of putting students on a trajectory toward adaptive expertise. I present results from the control and experimental conditions, but I focus the explanation on the results of the control conditions. They demonstrate how hard it can be to achieve an adaptive learner using relatively traditional forms of instruction. The control conditions, which look fine by measures of efficiency, are manifestly low on dynamic assessments of adaptiveness. By calling the control conditions, "traditional forms of instruction," I simply mean they are relatively common instances of instruction, which should be familiar to most readers.

Preparing to learn from lectures

The instructional goal of the first set of studies (Schwartz & Bransford, 1998) was to help university students learn eight behavioral findings about memory and their explanations (e.g., primacy, recency). We chose a control condition that is a prevalent form of instruction in higher education, where students first summarize an expository treatment before receiving the class lecture. In this case, the students wrote a 2-page summary of a chapter specifically written to describe the eight memory findings and their interpretations.

In the treatment condition, students graphed simplified raw data from classic experiments that exemplified the key memory concepts (a superb idea suggested by my doctoral advisor, John Black). They read a description of the different experimental conditions (e.g., immediate versus delayed recall). Their task was to graph whatever they thought were the important patterns in the data. They did not receive a rationale for the different experimental conditions, though we presumed they would think about them. The graphing and summarizing activities took roughly the same amount of time.

By looking at the graphs and the summaries, it was possible to code how many of the eight memory phenomena the students captured in these initial learning activities. The rates were nearly identical across the conditions. On the surface, it appeared that students had equal encoding of the key ideas regardless of the instructional activity.

Next, all the students received a common lecture that reviewed the empirical findings and presented the relevant theories. This lecture was the first stage of the dynamic assessment. About a week later, we measured what the students had learned. This was the second stage.

One post-lecture measure gave a true-false test on each of the memory concepts. For example, "For a list of words, people tend to remember the first words at a higher rate than the other words. True or False." Performances across conditions were nearly identical. They were also nearly 100% correct indicating that the students had learned all eight concepts regardless of what they had captured in their summaries or graphs. By this efficiency measure of correct recall, it appears that students had equal encoding and retrieval across the conditions.

The finding relevant to adaptiveness occurred on a spontaneous transfer measure called the "prediction task." The students received the description of an experiment, and they had to predict the results. The prediction task was designed such that all eight memory concepts were applicable. Table 1 shows the probabilities that students made a prediction using one of the memory concepts. The left-hand column shows the probability of using a memory concept on the prediction task when a student had noted the memory phenomenon in the graph or summary they produced prior to the lecture. Graphing the cases and then hearing the lecture nearly tripled the rate of transfer compared to writing a summary and hearing the exact same lecture.

The right-hand column of the table shows the probabilities that students would use a memory concept in the prediction task that they did not notice during the graphing or summary task. Did they pick up the missing information from the lecture? The students in the summary conditions learned very little from the lecture that they were able to use in the prediction task. This was not the case for the students in the graphing condition. They had a four-fold higher probability of using an idea presumably gained from the lecture than the summary students.

Mapping these results into Figure 1, summarizing a passage put students on Path R. These students learned enough

Table 1. Probability students would make a prediction conditionalized on whether they noted or missed a concept in their pre-lecture activity (Schwartz & Bransford 1998).

	Probability of prediction based on a memory concept	
	Noted in initial instructional activity	Missed in initial instructional activity
Exp A.		
Summary + Lecture	.26	.11
Graphing + Lecture	.74	.44
Exp. B		
Summary + Lecture	.23	.06
Graphing + Lecture	.60	.26
Graphing + Graphing	.18	.15

from the summary plus the lecture to do well on memory tests of what they had read and been told. However, the summarizing activity did not prepare the students to apply their knowledge to make predictions about a novel scenario. When these students had not identified a memory phenomenon during the initial summarizing activity, they had a negligible probability of picking up the relevant information from the lecture such that they could apply it to make predictions. In short, the lecture was relatively useless for preparing them to adapt. One may speculate that the summary students suffered from selective attention—during the lecture they paid attention to what they already knew from the summarizing activity.

It is important to note that the lecture per se is not responsible for the result. Experiment B, shown in the lower half of the table, included a condition where the students graphed the data a second time instead of hearing the lecture. The bottom row shows that they did poorly at the prediction task, even when they had noted the relevant memory phenomena in their graphing activity. The lecture was important for helping students adapt.

The students in the graphing plus lecture conditions were both effective on the tests of efficient memory and at adapting to the novel prediction task. The combination of the innovation experience of trying to notice and render patterns from the data coupled with the subsequent lecture appears to have put the students on Path A.

Preparing to learn from worked examples

The next studies used a worked example as the target learning opportunity (Schwartz & Martin, 2004). Worked examples are effective for helping students learn procedures (Cooper & Sweller, 1987). A verbal explanation of the procedural steps further helps students make associations that enrich their learning. By themselves, however, worked examples may not prepare student to adapt.

This pair of studies occurred with 9th-grade students who completed a 6-hour curriculum on statistical variability (Schwartz & Martin, 2004). Overall, the students learned quite well. At a one-year delay, the high-school students performed better on a variety of assessments compared to undergraduates who had taken a semester of statistics.

The experimental manipulations involved the final exam and one hour of the total instruction. After several days of joint instruction, the students separated. Half of the students were placed in a traditional Tell-and-Practice condition. They received a lesson that showed how to compare performances graphically across two different distributions, for example, high jump and long jump. The students then received a table of data and followed the same procedures to solve a new problem.

The other students were placed into an Invention condition. These students were presented with a similar problem scenario and the accompanying data. They tried to “invent” their own methodology for comparing the scores, which no one did very well. As smartly coined by Kapur (2014), these students had a *productive failure*. Despite their failure to produce the canonical solution, they were prepared for future learning (Bransford & Schwartz, 1999).

The second factor manipulated whether students had an opportunity to learn how to compute z-scores to compare across distributions. In the middle of the final exam, half of the students in each condition received a worked example. Following the example, the students’ task was to follow the worked example to compute a specific value with a new data set. Overall, 92% of the students were able to solve the subsequent problem with no treatment differences. Thus, by this measure of efficient outcomes, students in both conditions learned enough from the in-test worked example to replicate what they had been taught.

The other half of the students did not receive the worked example and its following problem. Their importance is for a measurement at the very end of the exam. All the students received a transfer question that asked them to compare performances across history (e.g., who was the better homerun hitter?). The question was whether students who received the worked example in the test would transfer its solution to help solve the new problem.

Table 2 exhibits the key finding in the rows for the Tell-and-Practice conditions. Based on the transfer measure, the Tell-and-Practice students learned nothing from the worked example compared to the Tell-and-Practice students who never received it. In contrast, the Invention students who received the worked example more than doubled the performance of otherwise similar Invention students who did not receive this learning opportunity. The Tell-and-Practice students did not pick up critical information from the worked example, whereas the Invention students did.

It seems unlikely that worked examples always fail to prepare students to learn from a second related example. In the current case, students could readily form an interpretation of the worked example that prevented them from seeing the new information it contained. The worked example in the test was highly related to what the Tell-and-Practice students had covered in class—they both involved comparing unlike outcomes using deviation units. Students may have thought they learned the main lesson in the classroom activity. For the worked example in the test, they focused on the information for completing the procedure rather than noticing what was new; namely, the ability to compute a specific z-score.

Preparing to learn from visual materials

My interpretation of the prior studies is that traditional instruction did not solve the challenge of information pickup,

Table 2. Percent of students who gave a workable solution on the target transfer problem by instructional treatment and learning opportunity (Schwartz & Martin, 2004).

	Percentage of students who succeeded on target transfer problem	
	Test with worked example	Test without worked example
Experiment A		
Tell-and-Practice	29%	32%
Invention	61%	30%
Experiment B		
Tell-and-Practice	22%	27%
Invention	46%	18%

which led to a lack of adaptiveness. The next pair of studies provides a more direct test of this interpretation by directly measuring what information students picked up from a visual worksheet.

The instructional goal of the study was to help 8th-grade students gain a deep understanding of ratio and proportion in the context of physical quantities (Schwartz et al., 2011). Density is the ratio of mass over volume, and speed is the ratio of distance over time. Ratio and proportions are big ideas that run throughout middle-school. In a Tell-and-Practice condition, 8th-grade students received a sheet with an explanation of density, examples, and lessons on how to compute it. In the Invention condition, students received a sheet with instructions that explained their task was to figure out how to make an index to compare crowdedness. The students then received the Crowded Clowns worksheet in Figure 2. In the figure, a given company uses the same ratio of clowns to bus compartments for each instance (i.e., the same density). The Tell-and-Practice students recognized this as a practice sheet for what they had been taught, whereas the Invention students were left to figure out how measure crowdedness.

Students worked in small groups in their respective conditions to find the crowdedness used by each of the companies. The next day, the students received a blank sheet of paper. Individually, their task was to redraw the Crowded Clowns worksheet from memory. Chase and Simon (1973) effectively used a redrawing measure to help evaluate what chess masters encoded from game boards compared to novices. Here, the question was whether the students encoded the ratio structure of density within each company. Borrowing from the analogy literature (e.g., Gentner et al., 2003), we called this the *deep structure*, because it is the relation of two features that defines each company rather than the

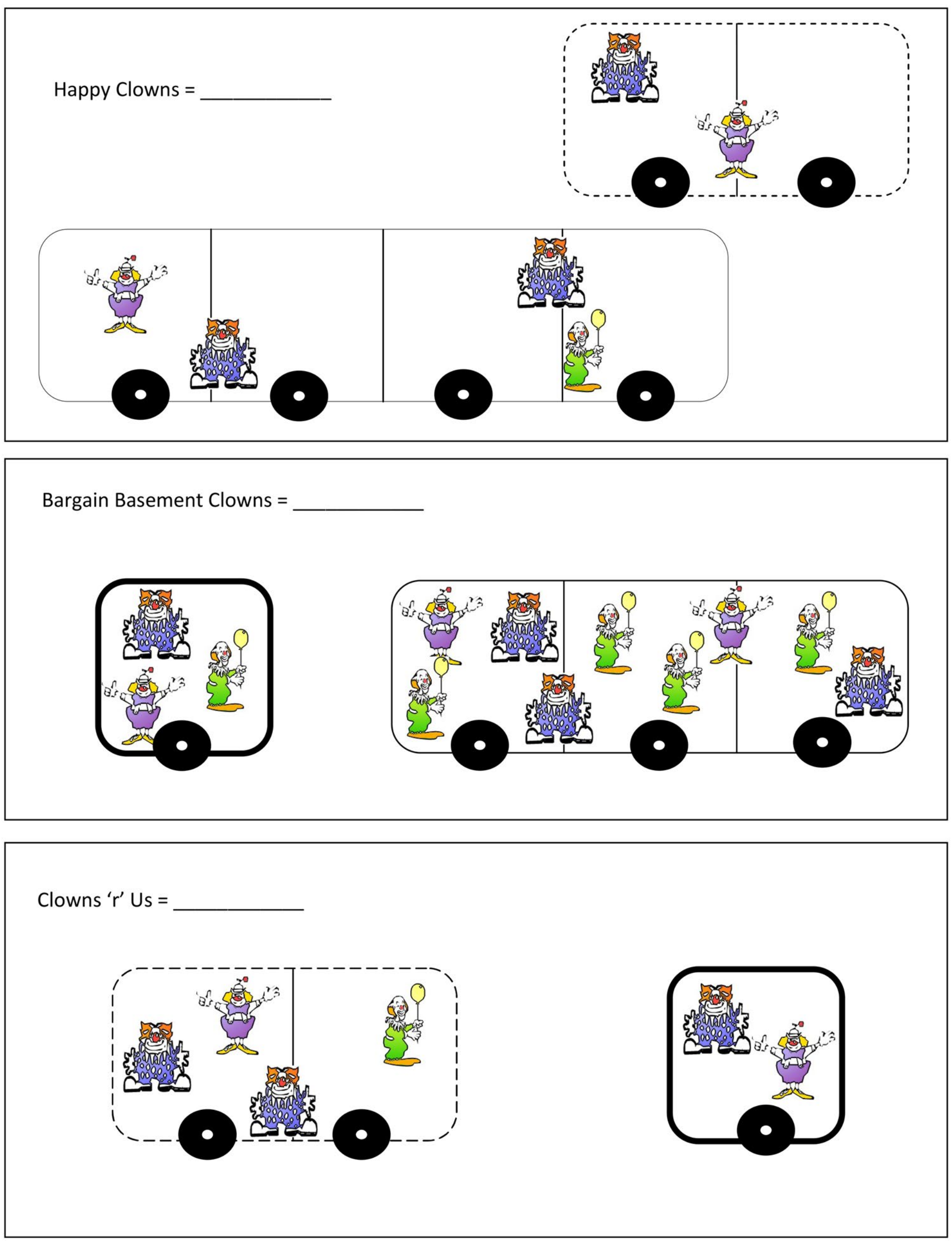

Figure 2. The Crowded Clowns worksheet students received (From Schwartz et al., 2011, Figure 1).

number of clowns or busses alone. In the language of perceptual learning, it would be called an *invariant under transformation*. The invariant is the ratio structure, and the transformation is the differences in the ratio across the companies. We also evaluated student recall of *surface features* incidental to the density of the clowns (e.g., dotted versus solid lines). Figure 3 shows examples of drawings that include deep structures and surface features.

The Invention students redrew roughly 50% more of the deep structures than the Tell-and-Practice students. In Experiment A, the percentages were 52% for the Tell-and-Practice condition and 76% for the Invention condition. In Experiment B, the percentages were 38% for the Tell-and-Practice condition and 59% for the Invention condition. This difference was not due to generally poorer encoding. Students across the conditions encoded similar numbers of surface features.

The favored interpretation is that many of the Tell-and-Practice students never perceived the ratio structure that is defining feature of density. Instead, they focused on efficiently executing the taught procedures rather than looking for novel information they never knew existed.

Students then completed more activities in their respective conditions, for example on speed. After several days, they received a common lecture on ratio-based quantities that showed how all the examples shared the property of ratio. They then practiced on word problems by computing density, speed, and so forth. Weeks later the students received a test of efficiency on the routines for computing and using ratios of physical quantities. The conditions performed similarly with good accuracy. Thus, the Invention activities did not come at the expense of efficient knowledge, and the Tell-and-Practice students did well on measures of the efficient application of what they had been taught.

Students also received a new situation that also involved ratios—the spring constant (mass over distance stretched). Students were asked to find the stretchiness of trampolines. The students in the Tell-and-Practice condition were 50% less likely than the Invention students to characterize stretchiness as a ratio of mass over distance. Instead, these students were more likely to use a single dimension, such as the distance stretched or the mass on the trampoline. They were not prepared to learn from the information embedded in the novel situation.

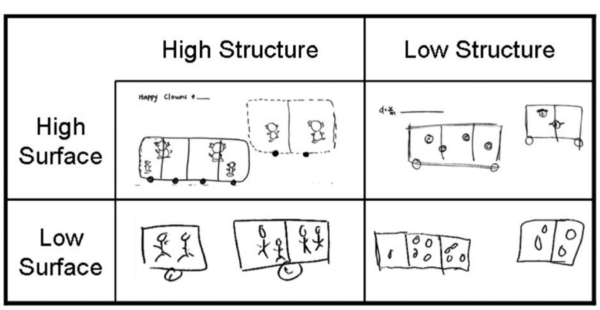

Figure 3. Examples of student drawings. The examples are coded by whether they exhibited the deep ratio structure and surface features. Low structure drawings did not exhibit proportionate ratios for a company (From Schwartz et al., 2011, Figure 5).

Interestingly, students in the lower half of the achievement distribution showed the greatest benefit of the Invention condition. They were four times more likely to adapt to the trampoline problem than their lower achieving peers in the Tell-and-Practice condition. This contradicts the common intuition that one should just tell lower achieving students what to do in the hopes they become more efficient. It may be better to let them innovate during early learning so they can solve the challenge of information pickup (see also Roll et al., 2018).

Summary of the three studies

Across three sets of studies seven years after each other (Schwartz & Bransford, 1998; Schwartz & Martin, 2004; Schwartz et al., 2011), students who received traditional forms of instruction were poorly prepared to pick up new information and adapt. In the first stage of a dynamic assessment, they were presented with new information in the form of a lecture, worked example, or visual material. They gained enough from these sources of information to succeed on measures of efficient application. They did not pick up information that prepared them to adapt to a novel problem at transfer. In the studies on learning from a lecture and worked examples, the students appeared to learn nearly nothing they could subsequently use to handle novel problems. In the studies on learning about ratios, many of the students failed to recognize the presence of ratios, even though they had been explicitly and repeatedly told how to find and compute them. They were on Path R toward routine expertise.

These studies are existence proofs that provide a cautionary tale. The way students are taught initially can have meaningful downstream consequences for their abilities to learn and adapt their knowledge in the future. We do not know conclusively if the traditional instruction failed to set the stage for adaptation, or whether it actively suppressed it. Studies by other scholars have demonstrated that early learning can interfere with future learning (e.g., Hallinen, 2015; Luchins, 1942). It could be interesting to conduct studies to examine this question, for example, by directly having students hear the lecture on memory without first completing the summarizing activity.

The pull toward routine efficiency

The three sets of studies supported the proposal of Path R in Figure 1. Instruction that emphasizes efficiency from the outset can put students on a trajectory toward routine expertise. In this section, I move away from grand theories to a level of analysis closer to the moment-to-moment experiences of learners, which may help to explain why the students in the traditional instruction did fine by efficiency measures of learning but not adaptive ones. In turn, this analysis helps to inform the subsequent section, which describes four principles for the design of experiences that start people on the path to adaptive expertise.

Natural forces draw people toward efficiency instead of unforced adaptation. The neuroscience literature includes many demonstrations that learning something unfamiliar depends on increased brain activation, whether measured by amplitude, duration, or overall recruitment of brain regions (Race et al., 2009). In contrast, the simpler act of remembering something increases efficiency for subsequent recall (Grill-Spector et al., 2006). From an evolutionary perspective, it makes sense that people would optimize on routine efficiencies rather than expend energy for a future that may never come. It is less biologically demanding to rely on knowledge one has already constructed than to generate new knowledge. Remembering is often easier than learning something new.

Of course, people do learn new things, and they do adapt to new environments. The drive toward cognitive savings is not absolute. Nevertheless, many educational settings create performance demands and knowledge organizations that play into people's tendency toward an efficiency trajectory.

Social factors create performance demands. Whether in the form of scripts or reward functions, situations of learning define the performance demands that shape people's effort. Students will optimize for the efficient retrieval of facts and procedures when classroom scripts and tests emphasize the replication of what one has learned. A telling example of students expecting efficiency-oriented performance demands comes from Taylor and his colleagues (2010). He developed a series of brainstorming tasks for his undergraduate biology class. For instance, students receive the scenario of rubber ducks spread across a swimming pool. Their task was to devise a method for getting all the ducks to the center of the pool without touching them. The scenario is an analog of the problem that cells solve when they bring distributed materials to the nucleus. I asked Taylor why the lesson took a detour to rubber ducks instead of the true cellular scenario. He told me he had tried to give the problem in the authentic biological context, but the students complained that he had not taught them the answer yet. Evidently, the students were used to problem-solving scripts in which learning was optimized for reusing what one had previously studied. Taylor et al. (2010) showed that by the end of his course the students improved in their spontaneous tendency to construct models to explain phenomena. They changed the optimization function, so students were becoming more innovative at creating their own explanations.

Psychological factors of knowledge organization also create challenges for seeking out new information. Ideally, people would self-detect that their knowledge could be improved by new information, even if they are giving correct answers. The organization of knowledge can make this difficult. For example, cognition "chunks" knowledge into ever more efficient consolidations (Anderson, 1982). These chunks can become black boxes that are difficult to decompose to reveal gaps and inadequacies (Slovic et al., 1972). More relevant to learning, educational materials often deliver relatively abstract chunks of propositional knowledge to start with. Students may not consider the details that go into those chunks, especially when the abstractions appear sufficient.

A relevant finding comes from Rozenblit and Keil (2002) who found that people over-estimate their explanatory knowledge, which they neatly termed *The Illusion of Explanatory Depth*. The account goes something like this: People learn a high-level description of a system. They take this description as sufficient, without appreciating that they do not understand the operation of the sub-systems that make the system possible. For instance, they might believe they understand automotive brakes, because they know that brakes use friction to slow down the wheels. They never think about the pistons, cables and fluid that make this possible, because they believe they know how the system works—through friction.

A concrete example of people's tendency to stick with efficient summary abstractions comes from a study on verbal and embodied knowledge (Schwartz & Black, 1996). Participants heard problems about touching gears. For example, *Five gears are in a row. If one turns the gear on the farthest left clockwise, what happens to the gear on the farthest right.* Participants completed a series of problems using different numbers of gears; 4, 3, 7, 6, 5, 9. At first people used their hands to model the problems by making various turning gestures. Eventually, they induced the abstract parity rule: Odd gears turn the same direction and even gears turn the opposite direction. Once they had the parity rule, they stopped gesturing. They had developed an abstract level of knowledge which generated very fast and correct answers.

In the second half of the study, participants received a new set of questions: *Five gears are arranged in a circle, so that each gear is touching its two nearest neighbors. If one tries to turn the gear on the top clockwise, what happens to the gear just to its left?"* The typical participant response was, "It will turn clockwise," using the parity rule for five gears. The experimenter then said, "That is wrong." Participants then said, "Counter-clockwise," using the parity rule for two gears or just guessing the opposite. The experimenter then said, "That is wrong." After some confusion, participants started to model the system with their hands again. Eventually, they discovered that odd numbers of gears in a circle lock. It took an overt failure for people to let go of their efficient abstractions and reengage the more laborious gestural simulation to generate new information.

Combined, performance demands and knowledge organization may explain why the control students in the studies did fine on routine tasks. They could solve computation problems and correctly judge statements about memory phenomena. Yet, they did not learn enough from the common lecture or worked examples to apply their knowledge to novel situations. The students were optimizing for the kinds of performance demands that many classrooms assess—cued retrieval tasks. The students were also content with the abstract level of knowledge they learned and there was no reason to seek new information. As the studies on learning ratio demonstrated, students often did not see that there was more information to be had, presumably because the abstract efficient knowledge they had—how to divide to get an answer—appeared sufficient.

Innovation activites for achieving an adaptive learner

A classroom environment that rewards efficient replication coupled with a psychological tendency toward "good enough" abstractions will not place students on Path A in

Figure 1. Path A proposes putting students on an innovation-first trajectory. The purpose of the innovation path is not for students to discover efficient solutions on their own. Instead, innovation tasks help skirt the pull toward efficiency while also yielding the key side-effect of addressing the challenge of information pickup. As the three sets of studies demonstrated, students can learn efficient solutions and theories through traditional instruction and without being trapped on Path R, if they engage in innovation tasks first.

The staircase of Path A should not be taken too literally. For example, there can be variations in the lengths of the line segments. Moreover, one might introduce some efficient knowledge to the students during an innovation task, for example, by giving a tip or showing why a solution will not work. Conversely, one might still ask students to solve "what if" problems during a predominantly efficiency-oriented task. Nevertheless, there are broad differences for how to establish the innovation segments of Path A. Loibl et al. (2017) provide a review of general instructional features of initial problem solving that support subsequent learning from a lecture. Kapur (2014) provides a comparison of the productive features of generative learning and explicit instruction. Here I focus specifically on four principles that guided the design of the innovation-first treatment conditions from the above studies. There are surely other effective approaches for putting students on Path A. For example, Arena and Schwartz (2014) created a videogame using the play pattern of the old videogame *Space Invaders* to help students discern properties of distributions. This prepared them to learn from a lecture on randomness.

To anchor the discussion, Figure 4 provides a representative task for introducing students to variance (cf. Schwartz & Martin, 2004). The cover story is that companies produce pitching machines. Companies need to label the consistency of their machine. A professional baseball player might want to buy a machine that is inconsistent. The parent of a younger child might want to purchase a consistent machine. The students' task is to innovate a way to compute a reliability index that can rate each machine.

For Figure 4, there was some art in choosing a topic where students would have sufficient intuitions to meaningfully engage the problem (e.g., consistency of baseball pitches); where they could generate multiple solution paths from relatively routine sources of prior knowledge (e.g., arithmetic); and, where the total number of cases was neither too many nor too few (e.g., six cases for four contrasts). I have not tried to theorize how to make these artful decisions, although this would be an excellent thing to do (e.g., Ashman et al., 2020). Instead, I highlight the four over-arching principles that distinguish this task from more traditional forms of instruction.

Ideally, the reader would consider Figures 2 and 4 together to pick up the relevant information in the examples and try to induce the four principles. By hypothesis, this would prepare the reader to learn from the following explanation more deeply and then subsequently use that learning in new contexts, for example, when trying to adapt the

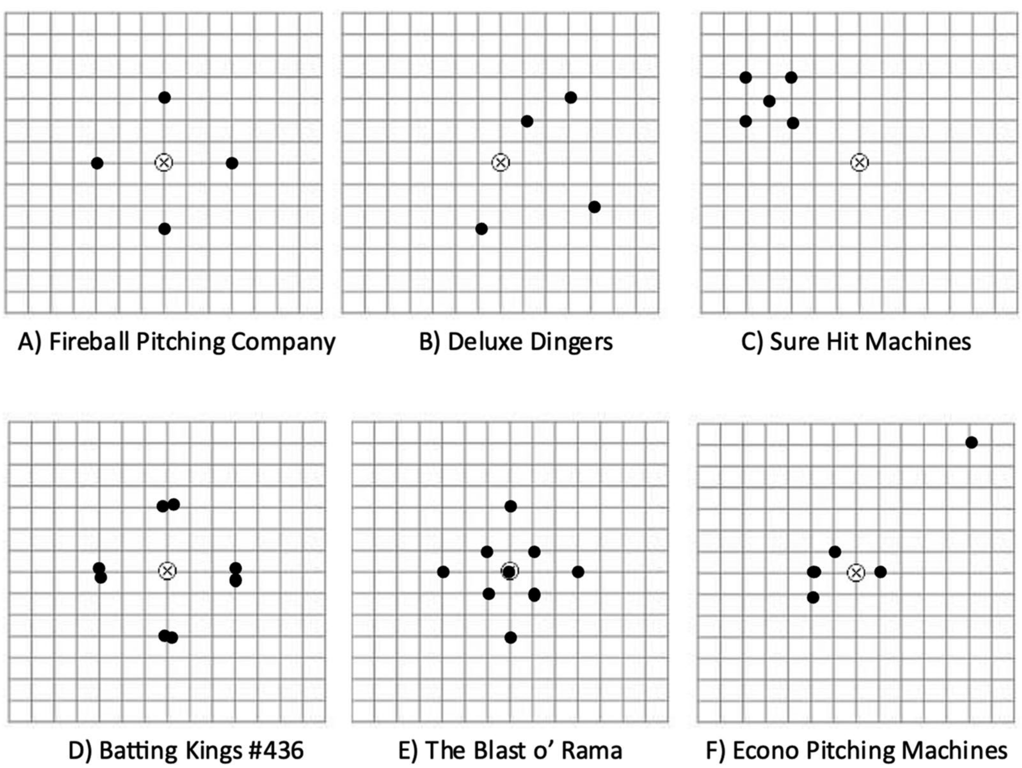

Figure 4. A representative innovation task. Students receive instructions that state: Here are six grids showing the results from six different baseball pitching machines. Each dot shows where a pitch landed. The X in the center shows the target. Your task is to invent a procedure for computing a reliability index for each of the pitching machines. There is no single way to do this, but you must use the same procedure for each machine to make it a fair comparison between the machines. Write your procedure and the index value you compute for each pitching machine.

instruction for a lesson on modern poetry. Of course, I appreciate that this is too much to expect of the gentle reader.

I have organized the four principles by the two *in situ* factors that might otherwise put students on Path R. One factor is the implied performance demands, and the other factor is the desired knowledge organization. I will focus on how the four principles help address these factors while also providing some practical advice for implementation. The are likely other positive outcomes that come with the four principles, such as a mindset for innovation. And, of course, there may be negative outcomes too.

Innovation performance demands to resist an efficiency default

Encourage innovation

Students are told that their task is to innovate their own representations and methodologies. One of the main consequences is that students will explore the situation to find information and structure. It is different from a performance demand to achieve a correct answer by replicating prior instruction efficiently.

I use Figure 4 in my introductory PhD statistics class (the full semester of materials through F-tests may be requested). Many of the enrolled doctoral students have taken a statistics course and they often try to shortcut innovation by trying to remember the formula. They search their prior knowledge rather than noticing the critical information in the problem situation. They are porting a performance demand that would put them on a trajectory to routine expertise. I ask them to resist the urge to look up their old formulas and instead try to figure out how to do it. After a few stairsteps of innovation followed by subsequent lectures and practice, students begin to recognize the innovation tasks as a useful, and typically enjoyable, way to learn.

Prevent early closure

People often just want to be done (Chin et al., 2019; Csikszentmihalyi & Getzels, 1970). In school, students can believe their task is to produce the correct answer and achieve closure. Early closure ends the search for new information. For the task in Figure 4, students rarely generate a foolish approach. They often come up with a reasonable partial solution. The risk is that they think they are done with their first solution and stop looking for other important information.

In practical experience, students need to work on problems like Figures 2 and 4 for 20- to 30-minutes to gain the benefits. Students do not need to discern all the information to benefit from the innovation activity. Nevertheless, the more they discern the better. Stopping after five minutes prevents them from picking up much of the relevant information.

One solution is to have students work in small groups of three or four students. Different students in the group often begin with a different pitching grid and each favors a different approach. Sharing across their solutions helps to keep the effort moving forward, which is one reason it is good to create a task that supports multiple solution approaches. A common refrain from one student to another is, “But how about this one? Does your solution work for it too?” Another instructional move is to walk around the room and generate an instance on the fly that the students’ solution cannot handle, and they need to address. With advances in artificial intelligence, it should be possible to generate cases automatically in response to a student’s proposed solution (Blair & Schwartz 2004).

Psychological supports for seeing beneath an abstraction

Include contrasting cases

Tasks that provide variation across a set of instances can help people discern precise informational structures. The inclusion of contrasting cases, like paint chips at the hardware store, can help people notice important dimensions of variation (Biederman & Shiffrar, 1987; POGIL instruction, Trout et al., 2008). When students contrast different pitching grids against each other, they notice properties of statistical distributions that the expert formulas were designed to handle. For instance, many students draw a line around the dots in Figure 4a. From there, they compute the area or perimeter. Figure 4e, however, alerts them to consider the density of the distribution, because a perimeter solution gives the same answers for Figure 4a and 4e despite their obvious differences. The Crowded Clowns worksheet in Figure 2 also includes targeted variation that alerts students to look beyond the surface. For example, the first and third companies each have an instance with two clowns. Ideally, this alerts students to the fact that they cannot just count the number of clowns to solve the problem.

Figures 4 and 2 provide contrasting cases for students. They do not depend on students generating their own informative data. There is an important place for learning the art of experimental design. However, these innovation tasks do not count on novices being experts at inquiry and gathering useful data. It is up to the instructional designer, perhaps with the help of a domain expert, to generate optimal contrasting cases.

One method for selecting contrasting cases begins with the target theory or formula. One can make contrasts to highlight quantities or relations that are captured by key variables and operations in the formula. For example, the standard deviation formula divides by n. Figures 4a and 4d make a contrast on sample size, which sets up the explanation that dividing by n handles sample size differences by taking averages. Figure 4c helps students consider the reference value for evaluating variability, which motivates why the standard deviation formula subtracts the data points from their own mean rather than a fixed reference value (such as the target X in the grids). When moving onto subsequent topics, such as Z-scores (i.e., measuring distances in standard deviation units), it is unnecessary to make contrasts on sample size, because students have already learned to pick up this information. Instead, contrasts on spread and centroids set up the Z-score formula.

Encourage a unifying account

Students should try to innovate a single account that works for all the cases. This can help them discern more complex information structures. For Figure 4, students need to come up with a single way to compute a reliability index that covers all the cases. For Figure 2 they need to come up with a single way to compute a crowdedness index. Ultimately, this is what the efficient solution or theory needs to accomplish. Working toward that goal may better prepare students to appreciate the solution when it is delivered.

Ideally, students would naturally seek a unifying account across a set of instances. Afterall, many of the ideas taught in school are intended to be general truths that span many instances. However, students may be more focused on efficiently solving the next problem, which yields piecemeal understanding tied to specific instances. A telling example comes from a study that gave college students a set of 12 patient cases on paper that described symptoms and diagnoses (Martin & Schwartz, 2009). Their task was to use these cases to help them diagnose computerized patients. Nearly every advanced student in a STEM field used the 12 cases to create a representation that would help solve future cases. For example, some made a table that had symptoms in the columns and diseases in the rows, and they would put checks in the appropriate boxes based on the 12 original cases. These students made a *prospective adaptation* by creating a unifying representation before they turned to diagnose their first computerized patient. In contrast, early undergraduates never organized the information in the original 12 cases to discern the underlying symptom structure. Instead, they flipped back and forth among the original 12 cases for each new computerized patient. They solved each problem individually.

Students may not realize they should expend the effort to come up with a general account that can handle the next case down the line (Rittle-Johnson & Star, 2007; Shemwell et al., 2015). Maloney (1988), investigating the learning of projectile motion, stated that student "rule usage was quite flexible with essentially no consideration of the fact that all of the situations involved the same type of motion. That is, the subjects seemed to treat each situation as unique with no need to correlate a rule on one task set with the rules on related tasks sets" (p. 511). As Gentner et al. (2003) concluded from their studies on analogical encoding, "learners cannot be counted on to spontaneously draw appropriate comparisons, even when the two cases are presented in close juxtaposition" (p. 403). Hence, the fourth principle creates the explicit goal of developing a unifying explanation across the cases (also see the MORE Thinking Framework, Trout et al., 2008).

Working toward a unifying account has two primary benefits for the challenge of information pickup. First, encouraging a unifying account provides a goal that helps students discern which information is relevant. Given the overabundance of information, it is hard to know what information is important without having a purpose in mind. The push toward a unifying account helps students consider what are incidental surface features they can set aside. It also encourages students to discern novel-to-them information structures that may not be apparent at first glance. To the point, in a study by Chin and colleagues (Chin et al., 2016), students received a set of contrasting cases involving projectile motion. In the innovation condition, the students had to come up with a way to predict an outcome for any case they might receive in the future, which was a way to motivate a unifying account across these and any other cases. In a compare-and-contrast condition, students received instructions to list similarities and differences across the cases. The compare-and-contrast students tended to list single dimensions that were familiar to them—distance, height, and speed. The innovation students combined dimensions into new quantities that reflect relations among variables (e.g., speed x height). They were more likely to pick up complex informational structures when asked to make a unifying account.

Second, the push toward a unifying account also provides a relatively natural way for students to self-correct their ideas by picking up more information. Students often generate a possible solution to handle a subset of cases. Afterwards, they look at additional cases and ask themselves, "Does my approach work for all the cases?" For example, does the perimeter solution for Figure 4a handle the denser distribution in Figure 4e? The task to make a unifying account provides a way for them to monitor their own knowledge and avoid the illusion of explanatory depth because they pick up information that puts their ideas to test.

Conclusion

One function of schooling should be to prepare students to continue learning so they can adapt to changing times and knowledge bases. The goal of adaptiveness requires special instructional considerations, because it runs into the challenge of information pickup; namely, people may never see what is new, and if they do not see what is new, they cannot adapt. Many current models of instruction and assessment overlook the special demands of information pickup. Three sets of studies demonstrated how instruction that does not address the challenge of information pickup was ineffective at preparing students to pick up new information. The students did learn when measured by sequestered tests of efficient retrieval and execution of prior knowledge. But the students from middle-school, high-school, and college showed little adaptation to new information provided in subsequent learning opportunities such that they could then adapt to a novel problem. A potential cause of the failure to pick up new information was the combination of performance demands and natural cognitive factors that drive people to rely on known efficiencies rather than appreciate new ideas and possibilities. The pull toward exploiting what one knows can prevent exploration of what one does not.

Early learning can start by engaging students in the phenomena. Asking them to innovate their own solutions drives them to pay closer attention to the situation. Afterwards, they can receive instruction that emphasizes efficient explanations and solutions, because they will be better prepared to learn from all they contain. Four instructional design principles can help students engage in innovation tasks to support the pickup of new information. Two principles addressed introducing performance demands that move students away from the common press toward efficiency: (1) Explicitly indicate to the students that the task is to innovate rather than recapitulate; (2) Help students resist the urge toward an early closure that ends learning. Two more design principles addressed creating tasks that support information pickup rather than memorization of abstractions: (3) Provide contrasting cases that hold targeted variation; (4) Ask students to make a unified account that handles the variation of the instances.

There are limitations to the research and claims I have presented. One limitation is a question of generality. The studies all emphasized learning in STEM domains, and it is unknown whether the findings generalize beyond the chosen topics and student populations. A second limitation involves the four design principles. My untested hypothesis is that these four ingredients work together and must be in play simultaneously to prepare students for future learning. For example, I doubt there will be much success in telling students to be innovative without providing a task that includes relevant information plus a clear goal. Similarly, providing contrasting cases with relevant variation will not work without the directive to innovate a unified account (Chin et al., 2016). The combinatorics of testing every possible combination of the four principles is prohibitive. Instead, one might conduct a "leave one out" study, where each condition ablates one of the four principles, and these reduced treatments are all compared to a condition that includes all four ingredients.

Another limitation is that I have not described the precise conditions when an educator should choose to use an innovation activity versus an efficiency activity. Presumably this depends on students' prior knowledge and abilities to discern relevant information. One might pursue an empirical approach to decide when to use an innovation activity. For example, show students a situation, wait an hour or so, and ask them to redraw it. If the students miss important information structures in the redrawing, then an innovation experience would be appropriate. More generally, if there are concepts where students exhibit regular misconceptions or difficulties year after year, an innovation experience could be helpful. With the development of more sophisticated computer technologies, one might imagine that an instructional technology could embed assessments that help the system decide whether a student needs an innovation experience or whether an efficiency experience would be better placed.

Finally, the presented studies were relatively short and confined to classrooms. Are the findings relevant to life beyond a given class? A compelling example comes from engineering professor, Noe Lozano, who took special responsibility for mentoring first-generation Latine engineering undergraduates. Lozano described the case of one young woman. In her first required STEM course, she did very badly on the mid-term exam. She must have been at the top of her high-school class to achieve admissions to the elite university. Being a committed student, she studied even harder for the next exam. Yet again, she did poorly. This triggered a cascade of self-doubt, including whether she belonged. I asked if this was a common story. He said, "Yes." When I asked why the student still did badly on the second test, he told me she had excelled in high school because she had learned how to "regurgitate information," and the college exams demanded more. I asked my colleague if she recovered from this first university experience. He said many of the students give up on their planned STEM careers after this typical experience, as did this young woman. He also said that for those who stick with it, it takes them about two years to adapt and regain their feelings of competence. I can only wonder if a different model of instruction in secondary school and college might have helped these talented students more easily achieve becoming an adaptive learner to pursue their dream trajectories to expertise.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The writing of this article was supported by the Klaus J. Jacobs Research Prize of the Jacobs Foundation.

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