Acquiring an Accurate Mental Model of Human Learning: Towards an Owner's Manual

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Abstract

To learn effectively requires understanding some fundamental, but unintuitive, properties of how the human learning and memory system works. A variety of research findings suggests, however, that human beings are prone to carrying around a mental model of learning and memory processes that is inaccurate and/or incomplete in some fundamental ways—owing, in part, to the implicit or explicit assumption that the storage and retrieval processes that characterize human learning and memory are similar to those that characterize man-made recording devices, such as a computer hard drive or a memory disk. Consequently, many humans engage in practices that yield short-term gains in performance but do not foster durable and flexible learning. The goals of this chapter are to say why and in what ways humans tend to misunderstand how to optimize their own learning and to provide a set of principles that are essential components of any owner's manual on how to learn and remember.

Keywords

Learning versus performance, desirable difficulties framework, forgetting, neuromyths, metacognition, New Theory of Disuse, distributed practice, interleaved practice, retrieval practice, errorful learning

Acquiring an Accurate Mental Model of Human Learning:

Towards an Owner's Manual

Knowing how to learn has always been important, but perhaps never more so than in today's ever more complex and rapidly changing world. In fact, knowing how to learn efficiently is a critical survival tool, not simply during our years of formal schooling, but across our lifetimes. We need to acquire new skills and update old skills, not only in our jobs, but also as we acquire new interests and hobbies—or, perhaps, want to help our children or grandchildren learn.

Research across the last several decades has revealed, though, that we can be prone to carrying around a faulty mental model of ourselves as learners, one that can lead us to prefer and carry out less effective learning activities rather than more effective activities. From one perspective, such findings are truly puzzling because one might expect that we would become expert learners based on what Bjork (1999, p. 455) called the "trials and errors of everyday living and learning." Said differently, it would seem that across the years of formal and informal education we would learn what works and what does not work. One might expect, too, that we would be taught how to learn by our parents or teachers, but parents and teachers are learners, too, meaning that they are also subject to being misled by the dynamics discussed in this chapter.

So why are people fooled? A very basic answer to that question is that the dynamics of human learning and memory are very complex and highly unintuitive, especially if one's intuitions are guided by the assumption that the storage and retrieval processes that underlie human learning and memory are similar to the storage and retrieval processes that characterize man-made recording devices, such as a video recorder or the typical computer. We may not fully understand the engineering details of such devices—that is, how they accomplish what they accomplish—but their functional architecture is far simpler and very unlike the functional architecture of human learning and memory. Any learner who assumes that the nature and consequences of the storage and retrieval processes that characterize human learning and memory corresponds to those of the typical recording device is going to manage his or her learning in far from optimal ways. Indeed, as surveys and other research indicates (e.g., Brewin, Li, Ntarantana, Unsworth, & McNeilis, 2019; Herculano-Houzel, 2002; Magnussen et al., 2006; Simons & Chabris, 2011, 2012), that assumption and numerous other inaccurate beliefs about human learning are quite prevalent today. Moreover, research that would correct such beliefs, courtesy of the *science of learning*—a burgeoning field that is investigating how human beings learn and how such processes can be optimized—is often not accessible to teachers (Organization for Economic Co-operation and Development, 2014), and in turn, to students, parents, and the general public.

When considering the need for improved educational outcomes on a wide scale—a recent United Nations-sponsored report noted, for example, that over 617 million children and adolescents globally are unable to achieve minimum proficiency in reading and mathematics despite largely having access to formal education (United Nations Educational, Scientific and Cultural Organization, 2019), and more than half of 4th, 8th, and 12th grade students in the United States do not meet minimum standards for subjects ranging from geography to history (National Center for Education Statistics, 2017)—the importance of fostering an accurate understanding of the dynamics of human learning and memory, and how to tailor learning activities accordingly, can hardly be overstated. In particular, teachers, learners and the general public are in need of an “owner’s manual for the human learning and memory system.” As a step towards developing such an owner’s manual, this chapter provides some important principles and relevant research.

Operational Benchmarks of the Human Learning and Memory System

When used to its full potential, the *human learning and memory system* excels at *learning*—that is, at fostering relatively permanent changes in behavior or knowledge that support long-term retention and transfer (Soderstrom & Bjork, 2015). Such learning may involve different types of information, skills, and more. *Retention* refers to the maintenance of knowledge and skills over time, such as across weeks, months, and years, and *transfer* refers to the ability to apply such knowledge and skills to a range of situations and tasks where they are relevant, versus simply to situations and tasks that match those present during training or instruction. Ideally, instruction and training produce learning that is both *durable* (i.e., retained over the long term) and *flexible*—that is, able to transfer to a variety of situations where what has been learned is applicable (Christina & Bjork, 1991). Learning activities that are under the learner's direct control—that is, *self-regulated learning*—should also support retention and transfer. When the system falls short—an all-too-likely outcome when we engage in suboptimal practices and use techniques that do not align with the system's operating principles—to-be-learned knowledge and skills tend not to be accessible over time or transferrable.

Basic Operating Principles that Users of the Human Learning and Memory System Need to Know

Cognitive scientists and computer scientists are striving to make computers store, retrieve, think, and reason in ways that are more human-like. That objective reflects the enviable capacities that humans have to absorb vast quantities of information from a wide array of sources and to achieve mastery of diverse topics ranging from academic subjects to languages and complex motor skills. From an artificial intelligence standpoint, humans can be thought of as "super intelligent computers" or "ultimate learning machines." Such lofty descriptions find support in the human learning and memory system's capacity to *acquire knowledge* (i.e., process sensory information and encode it into long-term memory storage); *develop skills* (i.e., attain proficiency in one or more task domains via study and practice) in multiple situations; *draw inferences* (i.e., integrate learning in a new way, such as forming a conclusion from two separate premises); and *transfer knowledge and skills* (i.e., successfully use prior learning in new situations)—all of which are, relatively speaking, unrivaled to date. Is the human-as-a-computer analogy, though, correct? As it turns out, largely not, at least with respect to existing computers.

The premise that human memory functions in ways similar to a computer or video camera, an analogy that 47-58% of the general public surveyed in the U.S. and Brazil endorse (Herculano-Houzel, 2002; Simons & Chabris, 2011, 2012), is central to many inaccurate mental models of learning. Even many highly influential information-processing models of learning and memory (e.g., Atkinson and Shiffrin, 1968), while otherwise helpful for conceptualizing the encoding, storage, and retrieval processes of the human brain, draw on that very comparison (Schmidt & Bjork, 1992). Other common beliefs and practices are consistent with the human-as-a-computer analogy. Many of us, for example, prefer training techniques that involve passively "feeding of information into the system" such as reading and reviewing—after all, if the brain is essentially a computer, then one should emphasize the process of exposing it to relevant information. More active and difficult learning methods are commonly left unused. In addition, we often focus on learning one skill at a time and assiduously avoid making errors—after all, when programming a machine to produce a response, one might have the machine repeatedly attempt that response and eliminate all imperfections until it achieves the desired result. In cases where we do impute non-machine characteristics to human learning processes, the emphasis is often on tailoring learning to purported individual differences in "learning styles" or even brain lateralization.

Decades of research in the learning sciences have contributed evidence that such beliefs and preferences can lead learners to adopt inefficient or even harmful learning practices. If one is to develop a truly informative mental model of the human learning and memory system, then a more accurate understanding of how we learn knowledge and skills, and how such processes differ from ordinary machines, is essential. Towards that end, the following section provides four basic principles that learners need to know in order to optimize the acquisition of knowledge and skills—that is, principles that an informed user of the human learning and memory system needs to know.

Principle 1: Learning Does Not Equal Performance

Imagine a semi-intelligent robot that is learning to copy a grasping movement. It engages in a fine-tuning process, over a series of practice trials, as it learns to recreate the correct motion. During that process, the observed *performance* (i.e., the behavior that can be measured during training) steadily improves. Ultimately, assuming that the robot is able to reproduce the movement perfectly, the robot's performance is a direct measure of the underlying *learning* (i.e., the relatively permanent changes in behavior or knowledge that instruction aims to achieve) that has occurred. More generally, when it comes to the acquisition of information and skills by computers and other machines, learning and performance are often synonymous. In the human learning and memory system, however, the two concepts are far from synonymous. In particular, although we can directly observe and measure human performance on many different tasks, we must *infer* whether learning, as measured by long-term retention or transfer, has actually occurred. The need to infer is particularly important because, unlike robots, the level of performance that a human being exhibits can greatly overstate (or, conversely, understate) the amount of learning that has occurred. Moreover, in human beings, current performance and long-term retention or transfer are often not correlated and can even, in some circumstances, be negatively correlated.

An abundance of empirical research—some dating back 80 years or more—not only reinforces the learning-versus-performance distinction but also reveals that performance can be a highly *misleading* indicator of learning (for reviews see Soderstrom & Bjork, 2013, 2015; for related theorizing see Bjork & Bjork, 1992; Estes, 1955a, 1955b; Guthrie, 1952; Hull, 1943, Tolman, 1932). Specifically, there are circumstances wherein learning occurs without apparent changes in performance, and the converse is true as well; that is, there are also circumstances when striking improvements in performance result in little or no learning (Bjork, 2009). The former is exemplified by instances of *latent learning*, wherein no performance improvements occur despite learning having taken place (e.g., Stevenson, 1954; Tolman, 1948; Tolman & Honzik, 1930); when fatigue masks learning improvements (e.g., Adams & Reynolds, 1954; Stelmach, 1969; see also Pan & Rickard, 2015); and when continued practice after a performance asymptote or limit has been reached, also called *overlearning*, improves overall learning as measured by subsequent long-term retention (e.g., Bromage & Mayer, 1986; Krueger, 1929, 1930). The latter is exemplified by cases wherein relatively easy training methods yield substantial speed and accuracy improvements that belie the minimal learning that is actually taking place. For instance, practicing the same athletic movement or the same type of math problem over and over can yield rapid performance improvements, but when those skills need to be used some time later and under other varied circumstances, the results are often far from optimal (for further discussion, see the next section). Each of these examples demonstrates that measurements of human performance during the learning process are far from reliable or direct measures of learning, such as post-training long-term retention or transfer.

A more accurate model of the human learning and memory system needs, therefore, to incorporate the learning-versus-performance distinction as a fundamental principle: Conditions that improve performance may not improve learning, and vice versa. From the 1930s through the 1950s, the major learning theorists of that time disagreed on many issues, but shared the view that a theory must distinguish performance from learning. Hull (1943), for example, contrasted the *momentary reaction strength* of a response (i.e., that which could be immediately observed, akin to performance) versus *habit strength* (i.e., the capability of exhibiting that response in the future, akin to learning), and Estes' (1955a) stimulus fluctuation model differentiated between *response strength* and *habit strength*, both of which map generally onto Hull's constructs (see also Skinner, 1938). More recently, Bjork and Bjork's (1992) New Theory of Disuse (NTofD) revived the learning-versus performance distinction by differentiating between *retrieval strength* (i.e., performance) and *storage strength* (i.e., learning) and formalized how the two strengths interact when some to-be-learned content is studied or retrieved.

Of most relevance to the present discussion, the NTofD assumes (i) that current performance is solely a function of current retrieval strength; (ii) that storage strength, which cannot be observed directly and must be inferred, is never lost; (iii) that retrieval, provided it succeeds, has a larger impact on both storage strength and retrieval strength than does restudy; and (iv) that there is an asymmetric interaction of retrieval strength and storage strength, which takes the form that the increases in retrieval strength that result from study or retrieval are larger the higher the level of storage strength, whereas—somewhat unintuitively—increases in storage strength are smaller the higher the level of current retrieval strength.

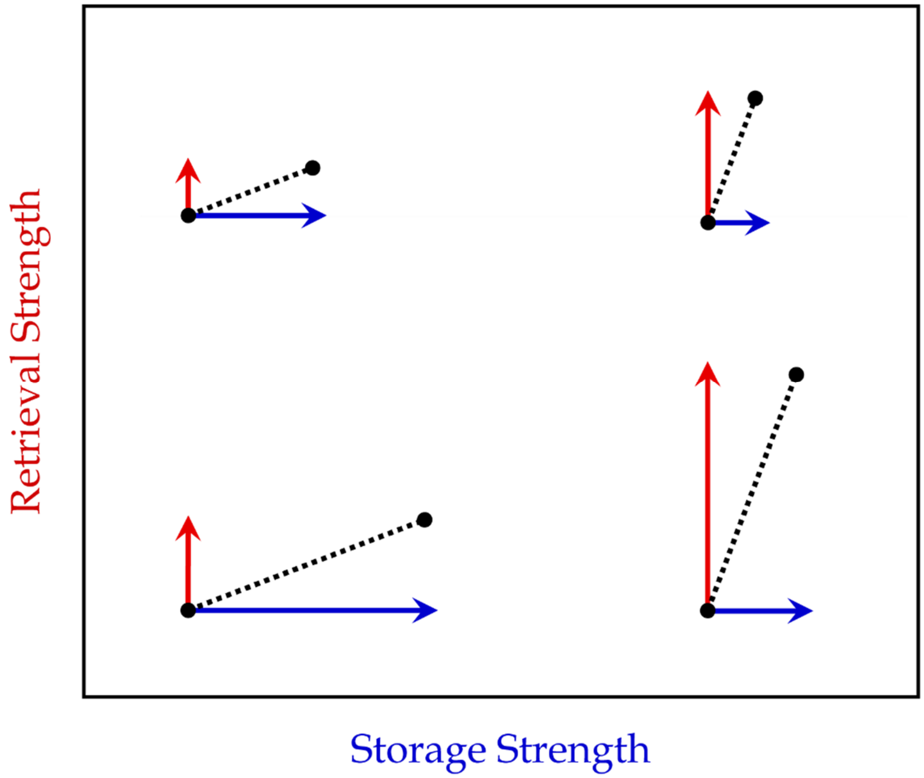

Figure 1. The effects of study and retrieval practice on *retrieval strength* (i.e., performance) and *storage strength* (i.e., learning) as predicted by the New Theory of Disuse (NTofD; Bjork & Bjork, 1992). According to the NTofD, the higher the storage strength, the greater the increase in retrieval strength; whereas, somewhat unintuitively, the higher the retrieval strength, the lower the increase in storage strength.

Thus, with respect to things learners need to know, the NToD—first and foremost—says that current performance is not to be trusted as a measure of learning (i.e., storage strength), that practicing retrieval processes is often a more productive activity than restudying, and that manipulations that decrease current retrieval strength, such as delaying (spacing out) when something is restudied can enhance learning (i.e., storage strength). Major predictions of the theory are depicted in Figure 1. The practical benefits of practicing recall, also called *retrieval practice*, and delaying restudy of information, also called *distributed practice*, are discussed further in subsequent sections of this chapter.

The longstanding and widespread predilection for learning techniques that typically generate high levels of performance, but are generally ineffective for retention and transfer, stems in part from a failure to grasp the learning-versus-performance distinction (Bjork, 1994a, 1999; Soderstrom & Bjork, 2015b). Such techniques—including, for example, repeatedly practicing the same skill in isolation (also called *massed practice* or *blocked practice*)—are appealing because the rapid performance improvements that they foster are intrinsically motivating (Ghodsian, Bjork, & Benjamin, 1997) and can generate the impression of highly successful learning. If human beings are analogous to computers or machines, then that impression would be accurate. In many cases, however, the impression of successful learning is illusory. Rather, the human learning and memory system is often better served by training methods that, by making the learning process initially more difficult (by decreasing retrieval strength), depress performance, but enhance learning (storage strength).

Principle 2: Difficulties Can Be Desirable

The human body often responds remarkably well to challenging physical activity. For example, after just a few calisthenics sessions, the cardiovascular, musculoskeletal, and respiratory systems adapt, yielding better responsiveness in future sessions. A lackadaisical training routine, however, typically yields fewer adaptations than a more intensive one. At a broad level, the human learning and memory system also benefits from more challenging, as opposed to relatively easy, training techniques. In fact, as a general principle, training techniques that reduce initial performance, as evidenced by lower accuracy, more errors, or greater forgetting, often substantially improve learning over the long term. Bjork (1994a, 1994b) described such conditions as *desirable difficulties* (see also Bjork, 1999; Christina & Bjork, 1991; Farr, 1987; Reder & Klatzky, 1993; Schmidt & Bjork, 1992) and recommended their use on a wide scale. A growing body of research on *evidence-based learning techniques*, which includes all of the desirable difficulties that have been discovered to date, is focusing on whether findings from laboratory experiments using simple to-be-learned materials and short retention intervals extend to realistic educational materials and intervals (for a review, see Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013).

Many, maybe most learners are unaware, however, that some difficulties are desirable and, instead, adopt learning practices that are the opposite of what Bjork and Bjork (2011, p. 56) described as “making things hard on yourself, but in a good way.” In surveys, 64-80% of U.S. undergraduate students report no role of formal instruction in their choice of learning strategies (Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007) despite instructors commonly stating that they discuss learning methods in class (79% surveyed by Morehead, Rhodes, & DeLozier, 2016). Rather, most choose learning strategies on the basis of intuition and improvisation (for discussion see McCabe, 2011). Moreover, when prompted to identify the learning techniques that they most often use, students commonly report rereading, cramming, highlighting, and other techniques that maximize one-time exposure to target materials—perhaps based on the flawed human-as-a-recording-device analogy—rather than more cognitively challenging activities such as distributing learning over time (e.g., Karpicke, Butler, & Roediger, 2009). In fact, of ten prominent learning techniques that cognitive and educational psychologists scrutinized in a recent in-depth literature review (Dunlosky et al., 2013; see also Pashler et al., 2007), popular strategies such as rereading received bottom-drawer “low utility” ratings. Just two techniques, retrieval practice and distributed practice, received the top “high utility” rating. Despite their strong efficacy, however, both techniques are among the least frequently used by students and are even discouraged—if, perhaps, inadvertently—by some teachers.

It appears, therefore, that to the degree a learner has a faulty mental model of how learning occurs, he or she becomes vulnerable to mis-assessing the relative efficacy of common study and training techniques. Although much remains to be uncovered about the conditions under which some evidence-based learning techniques are the most beneficial, ample research exists to identify several classes of techniques that provide challenges and appear to slow the rate of learning (as assayed by initial performance), but that actually improve or accelerate learning, and, hence, qualify as difficulties that are desirable (for discussions see Bjork, 1994aa, 1994b, 1999; Bjork & Bjork, 2011; Brown, Roediger, & McDaniel, 2014; Christina & Bjork, 1991; McDaniel & Butler, 2010; Schmidt & Bjork, 1992; Soderstrom & Bjork, 2015). Four prominent categories of desirable difficulties, each of which evokes a candidate operating rule of the human learning and memory system, are discussed next.

Distribute learning over time

In many learning situations there are various options regarding *when to learn* knowledge and skills and *how often to practice* a given target skill or body of information. For example, one could devote specific days of the week to studying for a particular course, plan and execute a practice schedule that leads to a high-stakes exam or performance evaluation, or even choose to revisit materials at a later point or not at all. What kinds of decisions do most human learners make in such cases? In surveys (e.g., Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007), just 11-13% of U.S. undergraduate students report planning out a specific *learning schedule* ahead of time. Moreover, approximately 53% confine all of their studying for specific sets of materials into one session before an exam, a pattern that is more formally categorized as *massed practice* (and if it occurs shortly before an exam, “cramming”). Further, a whopping 72-86% of students never revisit materials after a course has ended, although instructors commonly report urging them to do so and often do so in class (Morehead et al., 2016). An abundance of empirical research suggests that each of these methods of scheduling learning is suboptimal (for discussions see Bourne & Healy, 2014; Brown, Roediger, & McDaniel, 2014; Dunlosky et al., 2013; Pashler et al., 2007; Yan, Thai, & Bjork, 2014).

Empirical studies provide further evidence of the prevalence of suboptimal methods of scheduling learning. For example, Taraban, Maki, and Rynearson (1999) tracked undergraduate students' learning activities in introductory and upper-division psychology courses. Because the course materials could only be viewed via an active internet browser connection, exactly when and how long each student spent preparing for the course was recorded. The results provide a striking demonstration of cramming: Students spent a mere 0-5 minutes on average with course material in the weeks leading up to the exam, but on the day or two just prior, the average time spent spiked to over an hour. To many instructors, that pattern and other similar practices is not unique: Many students commonly plan and execute study schedules that involve engaging with learning materials no more than once. Even if students do plan otherwise, they often find it more realistic to engage in patterns that more closely resemble cramming (e.g., Blaisman, Dunlosky, & Rawson, 2017; Susser & McCabe, 2013). Moreover, such practices are not just restricted to poorly performing students or those that, for various reasons, have run out of time; for example, when students are convinced that they know the answer to specific questions, 54-64% deliberately choose not to re-engage with the questions (Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007; Morehead et al., 2016) and likely never revisit those questions even if they have opportunities to do so.

If human beings learned in the same manner as computers or other man-made devices, then such practices would be acceptable: When something is recorded twice on a man-made recording device, the way it is recorded the second time matches exactly how it was recorded the first time. In the case of human memory, on the other hand, how information is stored a second time it is studied (or, for that matter, a third or fourth time) can vary in ways that lead to more complete and durable memories. As a general operating rule, the human learning and memory system retains substantially more information for a longer duration when it learns over multiple sessions that are "spaced"—that is, distributed out in time—rather than massed. In fact, the finding that temporally spaced learning opportunities, or *distributed practice*, improves memory is one of the oldest discoveries in all of experimental psychology (often credited to Hermann Ebbinghaus, who first described the phenomenon in 1885), and is among the most robust of all psychological phenomena with over 250 successful demonstrations to date (including for verbal materials and motor skills; for reviews see Cepeda, Pashler, Vul, Wixted, & Rohrer, 2006; Crowder, 1976; Dempster, 1989; Lee & Genovese, 1988). Researchers have suggested various candidate mechanisms for why this *spacing effect* occurs, including encoding variability, consolidation, practicing retrieval from long-term memory, and others.

Distributed practice involves temporal spacing that might be on the order of minutes to months. The critical factor is that information should be learned more than once at different times (for a model of optimal spacing intervals across different spans of time, see Cepeda, Vul, Rohrer, Wixted, & Pashler, 2008). Even greater improvements in retention are likely if (i) there is more than one spaced learning opportunity (e.g., two or three learning sessions on different days), (ii) if learners practice recalling information rather than simply rereading or restudying, (iii) if there is the opportunity to revisit information even if it was already well-learned (e.g., Rawson & Dunlosky, 2011), and in some situations, (iv) when an *expanding retrieval schedule*—wherein the interval of time between successive practice sessions involving recall progressively increases—is used (e.g., Kang, Lindsey, Mozer, & Pashler, 2014; Landaurer & Bjork, 1978; cf. Karpicke & Roediger, 2007, 2010). In most cases, if a human learner is given a set amount of time to learn a set of materials, then dividing that time over one or more learning sessions, rather than expending it all in a single session, yields more durable learning.

One of the most impressive demonstrations of distributed practice's benefits involves a study by Bahrick and Phelps (1987; see also Bahrick, Bahrick, Bahrick, & Bahrick, 1993) wherein undergraduate students learned and practiced recalling Spanish vocabulary words during a single massed practice session, two or more sessions separated by 1 day, or two or more sessions separated by 30 days. Initial learning of the vocabulary words was more difficult under conditions involving distributed practice, and particularly for participants that experienced the longest time intervals between sessions. However, on a recall test administered a full eight years later—that is, 2,920 days after learning first occurred—the participants that had experienced the largest amount of spacing between sessions, namely 30 days, correctly recalled words at a rate that was 2.5 times greater than that following massed practice. That result, along with numerous other studies showing similar patterns, exemplifies the status of distributed practice as a truly desirable difficulty: Although the technique can be more challenging, at least initially, and is often more logistically complex to implement, distributed practice yields better learning and superior retention over the long term.

In many cases, learners adapt quickly to the greater difficulty during acquisition and logistical complexity that distributed practice often entails. A further challenge, however, involves learners' lack of appreciation of the benefits of distributed practice (for discussion see McCabe, 2011; for review see Son & Simon, 2012). The mistaken belief that massed practice is more effective than distributed practice has been repeatedly documented: Learners commonly rate massing as more efficacious than spacing, including for themselves and for others (McCabe, 2011; Simon & Bjork, 2001), although students sometimes give higher ratings to multi-session studying than cramming (e.g., Susser & McCabe, 2011). After having had the experience of learning under conditions of massed versus distributed practice, learners often continue to underestimate the latter's benefits (e.g., Kornell & Bjork, 2008; Kornell, 2009; Logan, Castel, Haber, & Viehman, 2012; cf. Wahlheim, Dunlosky, & Jacoby, 2011). An example from Kornell and Bjork (2008), in which learners trained to recognize visual categories via massing versus spacing, is illustrative: Learners' ratings of the effectiveness of the two methods were the reverse of the actual results.

Distributed practice also tends to yield lower learner satisfaction ratings (i.e., in terms of how enjoyable or preferable it is to experience) versus massed practice (e.g., Baddeley & Longman, 1978), possibly due to its greater difficulty. Conversely, the higher initial performance that is characteristic of massed practice can fool learners into assuming its greater efficacy (Bjork, 2009; Kornell, 2009; Schmidt & Bjork, 1992). If permitted to select between either scheduling method, however, whereas young children tend to indiscriminately opt for massed practice (e.g., Son, 2005), adults are more open to switching between the two schedule types (Son, 2004; Pyc & Dunlosky, 2010; cf. Benjamin & Bird, 2006; Toppino & Cohen 2010; Toppino, 2010), and in some cases will use distributed practice more often than would occur by chance (e,g,, Son & Kornell, 2009). Overall, if learners are to accept distributed practice as a desirable difficulty and begin to reap its benefits, then misconceptions about the technique must be dislodged from their mental models of human learning.

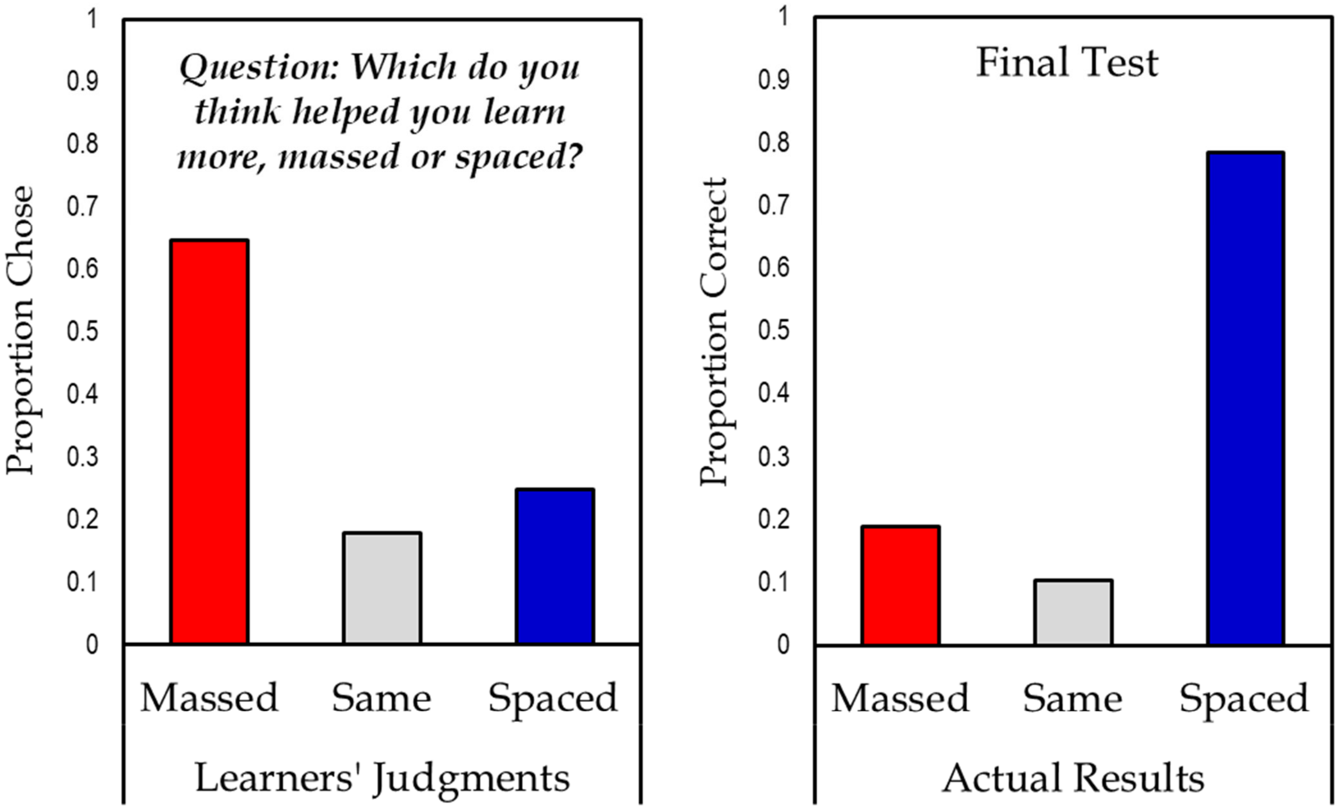

Figure 2. Effects of *massed* versus *spaced practice* on learners' beliefs and actual learning. Proportions of participants (left panel) who said there were better at identifying new paintings by artists whose paintings had been presented using massing/blocking versus spacing/interleaving, versus the actual proportions of participants (right panel) who were better at identifying new paintings by artists whose paintings had been shown massed/blocked versus spaced/interleaved. Results drawn from Kornell, N., & Bjork, R. A. (2008). Learning concepts and categories: Is spacing the "enemy of induction"?. *Psychological Science*, *19*(6), 585-592.

Vary the skills or materials being learned

Related to the aforementioned issues surrounding the use of distributed practice is the question of *what* specific materials to cover, or skills to practice, at a given point in time. Should learners focus on one particular skill or topic during each learning session (such as subject A on Mondays, subject B on Tuesdays, subject C on Wednesdays, and so on)? Or are there circumstances where it is more efficacious to tackle a series of different skills or topics during each learning session (such as subjects A and B on Mondays, subjects C and D on Tuesdays, and so on)? In surveys, 56-59% of undergraduate students report that their choice of materials to study is simply dictated by whichever is due soonest (Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007). For teachers, coaches, and students that are able to exercise substantial control over their learning schedules, another approach is popular: Focus on one skill or topic at a time. As evidenced by examinations of learning materials, curricula, and instructional practices, that segregation of learning into discrete blocks of time, or *blocked practice*, is widespread in such domains as mathematics instruction (e.g., Rohrer, Dedrick, & Stershic, 2015), second language learning (e.g., Pan, Tajran, Lovelett, Osuna, & Rickard, 2018), and sports coaching (e.g., Williams & Hodges, 2005), just to name a few.

Blocked practice, or blocking, is a form of massed practice in that the learning of a given skill or topic occurs during a contiguous period of time (the terms blocked practice and massed practice are sometimes used interchangeably, but blocking is also intended to convey that the practice or study of a given skill or topic is segregated from that on other skills or topics). Blocking entails little-to-no variation, with the same materials practiced over and over. It is a time-honored technique that appears to be the very embodiment of the adage “practice makes perfect” (Pan, 2015), or the advice that learners are often given to “work on one thing at a time.” Moreover, not only is blocking relatively easy to schedule and in alignment with common organizational principles (e.g., it is well-suited to the structure of most course syllabi), but it is also in keeping with a mental model of learning wherein repeated practice on a given skill or topic is assumed to be the most effective way to develop proficiency in that domain. The universality of that assumption, however, is flawed: A growing body of empirical research has found that a strategy of alternating between a set of related skills or topics during learning, or *interleaved practice*, is substantially more effective than blocking for learning in a variety of skill and content domains (for reviews see Brady, 1998; Carpenter, 2014; Carvalho & Goldstone, 2015; Kang, 2017; Lee & Simon, 2004; Magill & Hall, 1990; Rohrer, 2012; Wulf & Shea, 2002).

Unlike blocking, interleaved practice involves continuously alternating, or "interleaving," between different, if related, to-be-learned skills or topics. In other words, a variety of materials are learned at one time. Such interleaving can occur within one or more learning sessions. If a novice tennis player is learning the forehand, the backhand, and volleying, for example, then that player might practice using a schedule that alternates between single attempts of each skill (e.g., a "forehand-backhand-volley-forehand-backhand-volley…" pattern), as opposed to repeatedly practicing each skill in isolation (e.g., "forehand-forehand-forehand…" and "backhand-backhand-backhand…" patterns). That alternating pattern might be random or systematic (for discussions of the potential benefits of each, see Lee & Magill, 1983 and Pan, Lovelett, Phun, & Rickard, 2019). Crucially, interleaving tends to be more difficult during initial acquisition—in both learners' subjective impressions and in little-to-no improvements in performance—but as evidenced by measures of retention and transfer, can substantially improve learning over the long term (e.g., Hall, Domingues, & Cavazos, 1994; Kornell & Bjork, 2008; Pan et al., 2018; Rohrer & Taylor, 2007; Shea & Morgan, 1979).

The first empirical demonstrations of the benefits of interleaved practice, which largely occurred in the domain of motor skills, were referred to as *contextual interference effects* (Battig, 1966). That labeling reflected the observation that interleaving's efficacy is greatest when the to-be-learned skills are similar and presumably more likely to interfere with one another (Lee & Simon, 2004). In support of that conclusion, motor skill studies showing benefits of interleaving have largely involved cases where learners are attempting to master a set of related skills within a given sport—for example, batting practice with different types of baseball pitches (Hall et al., 1994) and learning different badminton serves (Goode & Magill, 1986). Subsequent investigations showing benefits of interleaving for cognitive tasks, including the learning of artists' painting styles (e.g., Kornell & Bjork, 2008), natural categories (e.g., Wahlheim, Dunlosky, & Jacoby, 2011), and mathematics skills (e.g., Taylor & Rohrer, 2010), have also featured sets of to-be-learned materials that share features and are highly confusable with one another (but not necessarily in all cases; for example, see Rohrer, Dedrick, & Stershic, 2015; Rohrer, Dedrick, Hartwig, & Cheung, 2019). These results have lent support to the *discriminative contrast hypothesis* (Kang & Pashler, 2012; see also Birnbaum, Kornell, Bjork, & Bjork, 2012), which ascribes the benefits of interleaved practice to a cognitive process involving comparisons between category exemplars. An alternate and possibly complementary account attributes the benefits of interleaving to distributed practice—that is, the temporal spacing between successive exposures or practice attempts involving to-be-learned skills or topics—that is inherent in an interleaved training schedule.

An example of the potential of interleaved practice to enhance cognitive skills comes from a study by Pan et al. (2018; see also Pan, Lovelett, et al., 2019) in which undergraduate students learned to conjugate verbs (i.e., modify verbs to reflect grammatical tense and other information) in the Spanish *preterite* and *imperfect* past tenses. In many language courses, verb conjugation skills are typically taught in a blocked manner, namely one tense at a time. Pan et al. compared two groups: A blocked group that learned to conjugate verbs in only one tense during each of two weeks, mirroring traditional methods, and an interleaved group that alternated between the two tenses as they learned over the same two-week period. As depicted in Figure 3, performance during each training session was approximately 30% higher in the blocked group, most likely due to the greater ease of practicing on only one tense. On a delayed test of verb conjugation ability (wherein students had to conjugate verbs in either of the two tenses, as fluent speakers are often expected to do in everyday conversation), however, the interleaved group scored, on average, 19% higher. These results not only suggest that interleaving is a viable method of learning verb conjugation skills more effectively, but also raise the possibility that interleaving may be an important tool to enhance learning in second language courses.

As with distributed practice, however, learners commonly fail to recognize or appreciate the benefits of interleaving. For example, Kornell and Bjork (2008) had participants experience both blocking and interleaving as they learned artists' painting styles from examples of the artists' paintings. Blocking the paintings by artist, versus interleaving the artists' paintings, was rated by 78-90% of the participants as equally or more effective than interleaving despite its being less effective (for similar results see Birnbaum et al., 2012; Pan et al., 2018; Pan, Lovelett, et al., 2019; Yan, Bjork, & Bjork, 2016; Yan, Soderstrom, Seneviratna, Bjork, & Bjork, 2017; cf. Wahlheim et al., 2011). Similarly, when given the opportunity to select the type of learning schedule that they would prefer to use to learn a set of natural categories or artists' painting styles, learners overwhelmingly chose blocking (Tauber, Dunlosky, Rawson, Wahlheim, & Jacoby, 2015; Yan et al., 2017). These suboptimal choices may stem from preexisting beliefs in the superiority of blocked and massed practice, as well as the ease of processing information, or *subjective fluency*, that blocking provides (Kornell & Bjork, 2008; Yan et al., 2016). As with other desirable difficulties, dislodging these incorrect beliefs from mental models of learning is necessary in order for interleaved practice to be adopted into broader use.

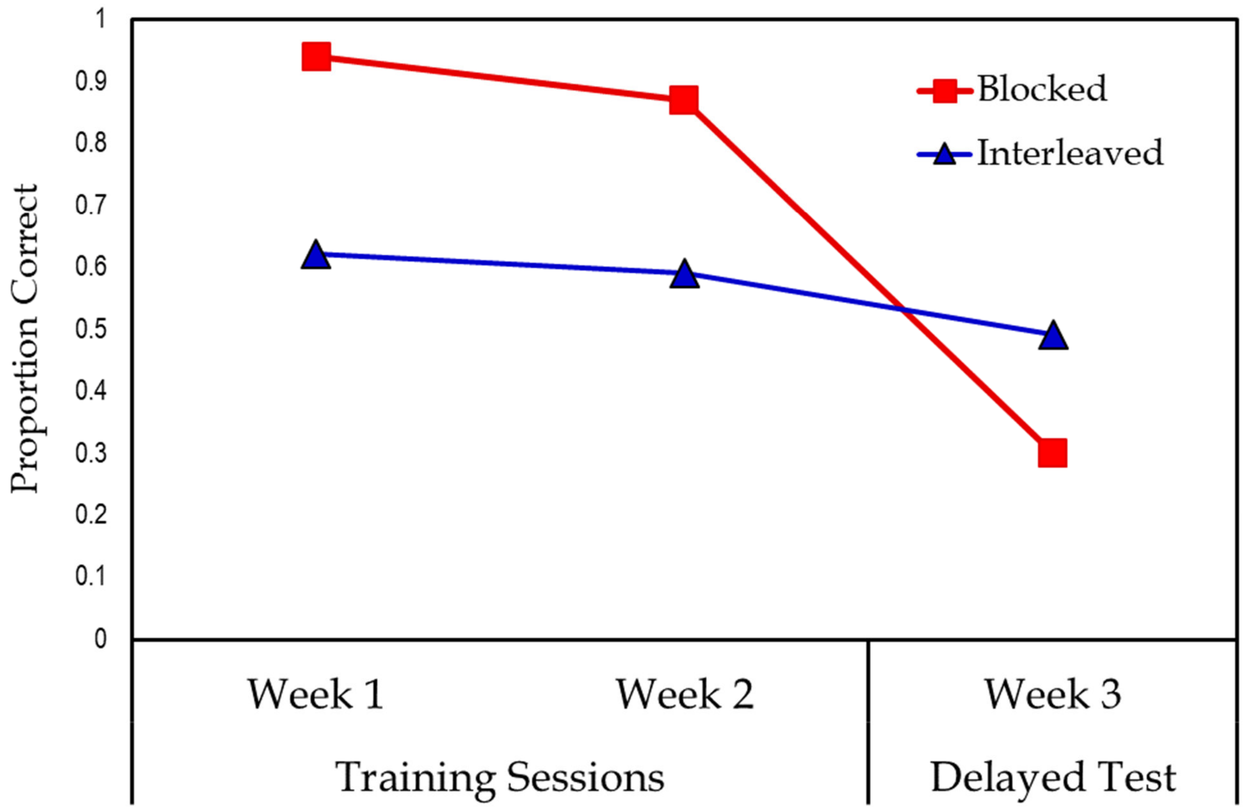

Figure 3. Effects of *interleaving* versus *blocking* on second language grammar skills. Across a two-week period, participants used interleaving or blocking to learn to conjugate verbs in Spanish. Blocking yielded higher accuracy than interleaving during training, but that pattern was reversed on a delayed test of verb conjugation ability. Figure adapted with permission from the American Psychological Association. Source: Pan, S. C., Tajran, J., Lovelett, J., Osuna, J., & Rickard, T. C. (2018). Does interleaved practice enhance foreign language learning? The effects of training schedule on Spanish verb conjugation skills. *Journal of Educational Psychology*.

Beyond interleaved practice, other training methods that also involve variation of some kind can also enhance learning. For example, increasing the variety of examples that are practiced can enhance the ability to solve problems involving analogical transfer (e.g., Gick & Holyoak, 1983) or anagrams (e.g., Goode, Geraci, & Roediger, 2008). For motor skills, varying the location from which one attempts to hit a target (Landin & Hebert, 1997), or varying the target location itself (e.g., Kerr & Booth, 1978), can be beneficial. Even varying the environmental context in which one studies information, such as the room or the individuals that are present, can be helpful (e.g., Smith, Glenburg, & Bjork, 1978; for a replication see Imundo, Pan, Bjork, & Bjork, 2019; for reviews see Bjork & Richardson-Klavehn, 1989; Smith & Vela, 2001). Collectively, these findings suggest that the beneficial impact of variation on learning, which constitutes an operating rule of the human learning and memory system, holds broadly across different instantiations of that rule (Christina & Bjork, 1991; Schmidt & Bjork, 1992; Soderstrom & Bjork, 2015).

Practice retrieving information from memory

Besides questions surrounding how to schedule learning, another very important question involves the activity or activities that one should engage in while learning—that is, *what one should be doing* while learning knowledge and skills. Surveys have shown varying levels of popularity for a variety of common learning methods, including summarization, copying, highlighting, and more. One technique, however, commonly tops the list (Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007; Morehead et al., 2016; see also Bartoszewsi & Gurung, 2015): 66-89% of students at levels ranging from secondary school to undergraduate education report the frequent use of *rereading*—that is, repeatedly reading course materials or other information (in some cases, the terms rereading, restudying, and reviewing are used interchangeably, with all three terms often referring to the same or similar activities). In several surveys, rereading even ranks as students' top learning strategy (e.g., Dirkx, Josefina, Camp, Kester, & Kirschner, 2019; Karpicke, Butler, & Roediger, 2009). It is perhaps fitting then that rereading and restudying are often the methods that first come to mind when one hears the phrases "studying for a class" or "study techniques." Even the word "study" can imply such methods.

Given a flawed mental model wherein the process of storing information in human memory is assumed to be similar to storing information on recording devices or computers, rereading can seem quite sensible. Such a model is likely to include the notion that the more one is exposed to information, the more ingrained it becomes in memory, and is also likely to include the idea that any gaps in knowledge from an initial encoding event, such as if there were momentary interruptions in sensory data or other distractions, might be filled in via the repeated exposure that rereading provides. A body of empirical research, however, reveals that although rereading (and reviewing) can yield some learning benefits (e.g., improved memory after the second reading of a text as in Rawson & Kintsch, 2005), those benefits are minimal-to-nonexistent in many cases and may not accrue from multiple attempts (e.g., Callendar & McDaniel, 2009). In fact, in-depth reviews have concluded that rereading is generally inefficient and ineffective (Dunlosky et al., 2013; Pashler et al., 2007).

An alternate technique—one that is, in many ways, the polar opposite of rereading—does however reliably enhance learning. That method, *retrieval practice*, involves attempting to recall information from memory, such as by cueing with flashcards or taking a practice test. The results of that action are emblematic of another operating rule of the human learning and memory system: Retrieval is a “memory modifier” (Bjork, 1975, p. 123). Specifically, the act of retrieving information from memory does not result in a verbatim replaying of that memory, as occurs with computers or video cameras (and contrary to the belief that memories are immutable, which 29-40% of respondents in some surveys endorse per Simons & Chabris, 2011, 2012). Rather, retrieval practice strengthens the later *accessibility* of information in memory, in part by decreasing the access of competing information, which Anderson, Bjork, and Bjork (1994) labelled *retrieval-induced forgetting*.

The finding that retrieval practice enhances learning, a phenomenon that is more commonly known as the *testing effect*, ranks alongside the effects of distributed practice as among the most robust phenomena in all of psychological research (for reviews see Dempster, 1996; Dunlosky et al., 2013; Roediger & Butler, 2011; Roediger & Karpicke, 2006; Roediger, Putnam, & Smith, 2011; for meta-analyses see Adesope, Trevisan, & Sundararajan, 2017; Pan & Rickard, 2018; Rowland, 2014). Numerous theoretical accounts have been proffered to explain the effects of retrieval practice, including gains in the storage strength of retrieved items (e.g., Halamish & Bjork, 2011; Kornell, Bjork, & Garcia, 2011), the elaboration of memory traces (Carpenter & DeLosh, 2006), updating of contextual features (Karpicke, Lehman, & Aue, 2014), the formation of new memories (Rickard & Pan, 2017), and others. Crucially, retrieval practice is not a passive activity wherein learners simply process external information. Rather, in a process that is often more challenging than rereading or reviewing, learners make efforts to recall what they have previously learned, and in doing so, actively strengthen later access to that information.

The benefits of retrieval practice have been successfully demonstrated in over 200 studies to date, including for diverse sets of materials ranging from vocabulary words to images (for a listing, see Rawson & Dunlosky, 2011), at extended retention intervals (e.g., Carpenter, Pashler, & Cepeda, 2009; Pan, Cooke, et al., 2019), with learners of different ages and memory abilities (e.g., Meyer & Logan, 2013; Pan, Pashler, Potter, & Rickard, 2015), in classrooms (e.g., Jones et al., 2015), and relative to rereading (e.g., Carrier & Pashler, 1992), highlighting (e.g., McDaniel, Howard, & Einstein, 2009), concept mapping (e.g., Karpicke & Blunt, 2011), and other methods. Multiple forms of retrieval practice have also been shown to be effective, including practice-test formats such as free recall (e.g., Darley & Murdock, 1971), short answer (e.g., Duchastel, 1981), recognition (e.g., Hogan & Kintsch, 1971), and multiple-choice (e.g., Little, Little, Bjork, &

Angello, 2012), as well as via open and closed-book tests (e.g., Agarwal, Karpicke, Kang, Roediger, & McDermott, 2008), via purely mental recall attempts (e.g., Smith, Roediger, & Karpicke, 2013), and more.

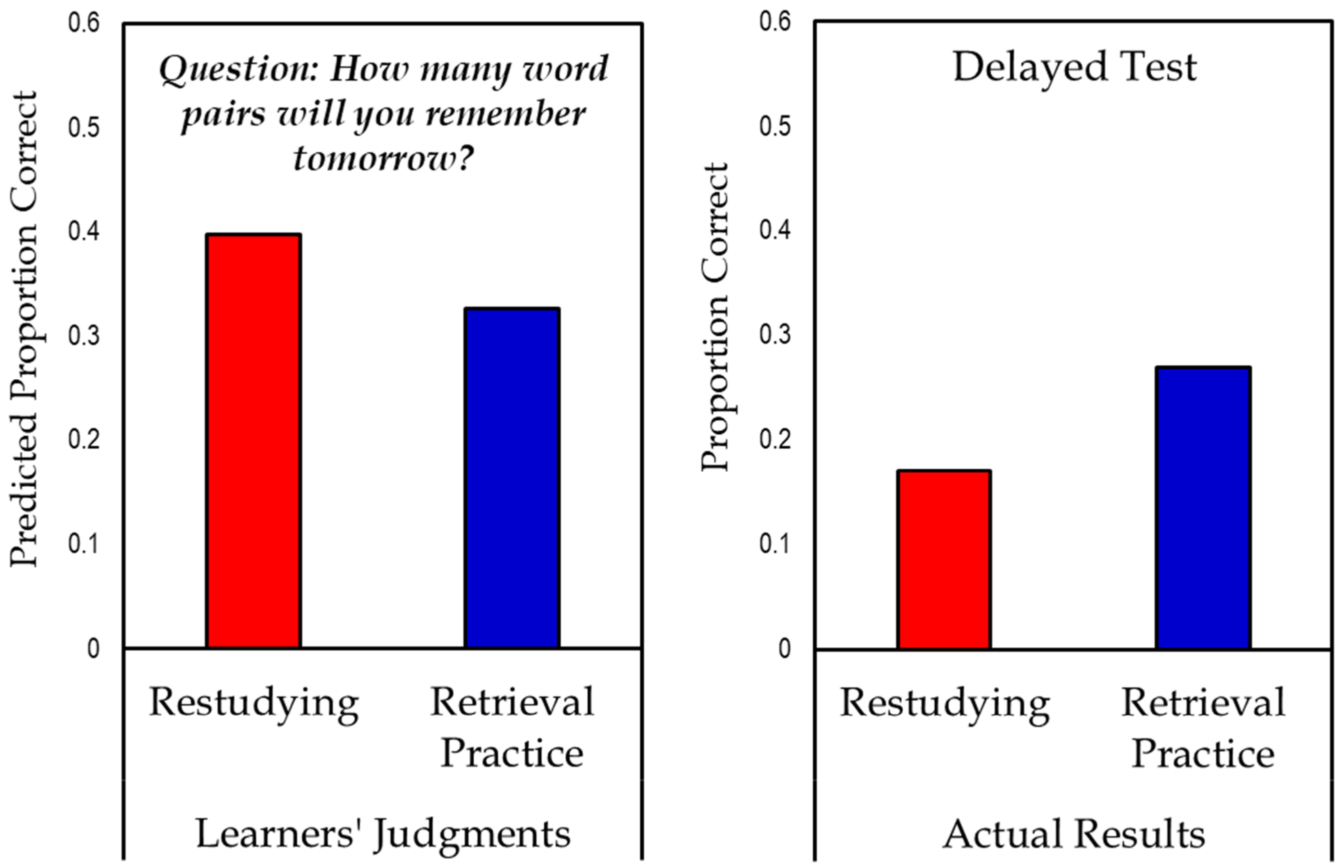

Figure 4. Effects of *restudying* versus *retrieval practice* on learners' beliefs and actual learning. Participants used restudy or retrieval practice to learn English word pairs and then estimated how well they had learned using the two techniques. Learners predicted greater recall of restudied word pairs on a 24-hr delayed test (left panel), whereas the opposite actually occurred (right panel). Figure adapted with permission from Springer Nature. Source: Tullis, J. G., Finley, J. R., & Benjamin, A. S. (2013). Metacognition of the testing effect: Guiding learners to predict the benefits of retrieval. *Memory & Cognition*, *41*(3), 429-442.

Besides the robust effects of retrieval practice on retention, a growing body of research has demonstrated that the technique can also improve transfer as well (for review see Pan &

Rickard, 2018). For instance, practicing recall can enhance learners' ability to apply knowledge to new scenarios (e.g., Hinze, Wiley, & Pellegrino, 2013), draw inferences (e.g., Eglington & Kang, 2018), and in the case of medical education, even treat new patients more effectively (e.g., Larsen, Butler, Larson, & Roediger, 2013). A notable example involves a study by Butler (2010) in which students read encyclopedic text passages and then retrieved or restudied concepts from those passages. A week later, a transfer test was administered wherein the students had to apply what they had learned to solve new application questions. The questions were especially challenging in that they were drawn from a different knowledge domain that the students had not previously learned (for example, given training on a passage about bats, the transfer test featured questions about aircraft; students had to generalize what they had learned from bats to aircraft). Prior training using retrieval practice resulted in 24% average better transfer test performance than prior training using rereading. That result is not just another example of retrieval practice's impressive capacity to support transfer; it is one of the few demonstrations of successful *far transfer*—that is, from one knowledge domain to another—in the entirety of learning research.

Unlike some other desirable difficulties, retrieval practice is, in fact, relatively widely used in the form of practice quizzing and flashcards. Surveys reveal that 60-72% of students list self-testing as a common learning strategy (Dirkx et al., 2019; Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007; Morehead et al., 2016). The most commonly stated reason for engaging in retrieval practice, however, is diagnostic; 49-64% report using practice tests to determine how much one has learned and/or the efficacy of prior studying activities. Such motivations are in keeping with the traditional function of tests, which are primarily used for assessment. One exception involves flashcards, which 60% of students in one survey reported using to aid memorization (Wissman, Rawson, & Pyc, 2012; although see Husmann & O'Loughlin, 2019).

Additionally, only 18-27% of surveyed students endorse retrieval practice as more effective than restudying, and in one study, 57% even stated that they would prefer to restudy than practice retrieval (Karpicke, 2009). Similarly, when learners are given the opportunity to experience both restudying and retrieval practice, they tend to underestimate the benefits of the latter (e.g., Kornell & Son, 2009; Tullis, Finley, & Benjamin, 2013), as shown in Figure 4. It is therefore the case that retrieval practice is not an entirely forgotten or overlooked desirable difficulty. Rather, it is a misunderstood one, and another example of the need to modify mental models of human learning to more accurately reflect its operating principles.

Treat errors as learning opportunities

Human beings generally share, and often reinforce by warning against or punishing, an aversion to making errors or mistakes. That aversion is justified in many circumstances—after all, errors can often lead to damaging and undesirable consequences. It is perhaps unsurprising then that the avoidance of errors is prominent in many learners' mental models and in a wide variety of education and training contexts: As examples, teachers and students in mathematics courses in the U.S. often minimize and avoid discussing errors (Stevenson & Stigler, 1994; Stigler & Hiebert, 2009), some military training programs actively discourage the committing of errors from the outset of instruction (Bjork, 2009), and in professional domains such as nursing, practitioners often have a defensive reaction to making errors and avoid discussing them entirely (Meurier, Vincent, & Parmar, 1997). Further, given that errors are often rare or completely absent after expertise in a skill has matured, a goal of avoiding errors during training would seem to be sensible. Even some prominent 20th century psychologists (e.g., Bandura, 1986; Skinner, 1953; see also Ausubel, Novak, & Nanesian, 1968), spurred by the now disproven belief that making errors always increases the likelihood of their recurrence, maintained that errors should be entirely avoided. That wholescale aversion to errors is, however, unjustified. In fact, a growing body of research (for review see Metcalfe, 2017) has revealed another operating rule of the human learning and memory system: Training conditions that allow for and even foster the occurrence of errors can be desirable for improving retention, transfer, or both.

Research on learning from errors provides some support for the aphorism that “mistakes are the best teachers”—that is, errors and mistakes are perhaps not always the *best* teachers, but are often quite helpful nonetheless. For instance, a series of empirical studies has demonstrated that failing to provide the correct answer to a question (such as the location of a country or the name of a particular person), followed by viewing the correct answer, often yields better memory for the answer than simply viewing the answer from the outset (e.g., Kornell, Hays, & Bjork, 2009; Pan, Lovelett, Stoeckenius, & Rickard, 2019; Richland, Kornell, & Kao, 2009). In other words, making errors can improve retention relative to not making any errors at all, as long as the errors are followed by correct answer feedback (Hays, Kornell, & Bjork, 2013). Typically, the question and correct answer have to be semantically related in order for the error generation and feedback process to yield learning benefits (e.g., Grimaldi & Karpicke, 2012; Huelser & Metcalfe, 2012; Knight, Ball, Brewer, DeWitt, & Marsh, 2012), a pattern suggesting that the to-be-learned materials should correspond to background knowledge levels that enable plausible, if incorrect, guesses. The benefit of making errors for memory is often especially strong for errors that are made with high confidence (e.g., Butterfield & Metcalfe, 2001, 2006; Cyr & Anderson, 2013; Metcalfe & Finn, 2011, 2012). That phenomenon, known as the *hypercorrection effect*, may stem from the heightened degree of surprise that learners experience upon seeing the correct answer (e.g., Fazio & Marsh, 2009).

Besides improving retention, error generation followed by feedback can also improve transfer. For example, Ivancic and Hesketh (2000) had trainees practice driving through a 4.8-kilometer roadway course on a driving simulator. The course featured a series of potential obstacles, including blocked lanes, blind curves, and high winds. In the error training group, trainees were immediately stopped and notified (in the form of a police siren and ticket) if they had engaged in any unsafe driving maneuvers, such as negotiating a curve at excessive speed. In the errorless training group, trainees completed a version of the course that was modified such that the obstacles, although still present, did not prevent trainees from reaching their destination, and the trainees were not stopped for their driving behaviors in any circumstance. On a subsequent test involving a different set of obstacles, the error training group exhibited safer driving behaviors, better ability to negotiate each of the obstacles, and fewer crashes overall. That result illustrates the value of learning from errors, both in terms of improved subsequent performance and better ability to handle new challenges. Similar results have been obtained for the case of problem-solving practice (e.g., Kapur, 2008; Kapur & Bielaczyc, 2012; see also Van Lehn, Siler, Murray, Yamauchi, & Baggett, 2003), wherein initially attempting and failing to solve a difficult problem in domains such as physics, followed by practice in effective solution strategies—a strategy known as *productive failure*—can improve the ability to solve new problems (relative to a strategy of practicing with easily-solved problems or receiving more detailed instructions from the outset).

Although formal research on learners' beliefs regarding the utility of making errors is currently sparse, there is some empirical evidence that the value of errors as educational tools is substantially underappreciated: For instance, Huelser and Metcalfe (2012; see also Potts & Shanks, 2014) reported that undergraduate students consistently rated error generation followed by immediate feedback as less beneficial than simply studying correct answers. That pattern, which is depicted in Figure 5, held in cases where learning from errors doubled the rate of successful recall on a retention test. The finding that learners do not recognize errors as learning opportunities is also broadly consistent with the aforementioned anecdotal evidence of the widespread aversion towards, and de-emphasis of, making errors.

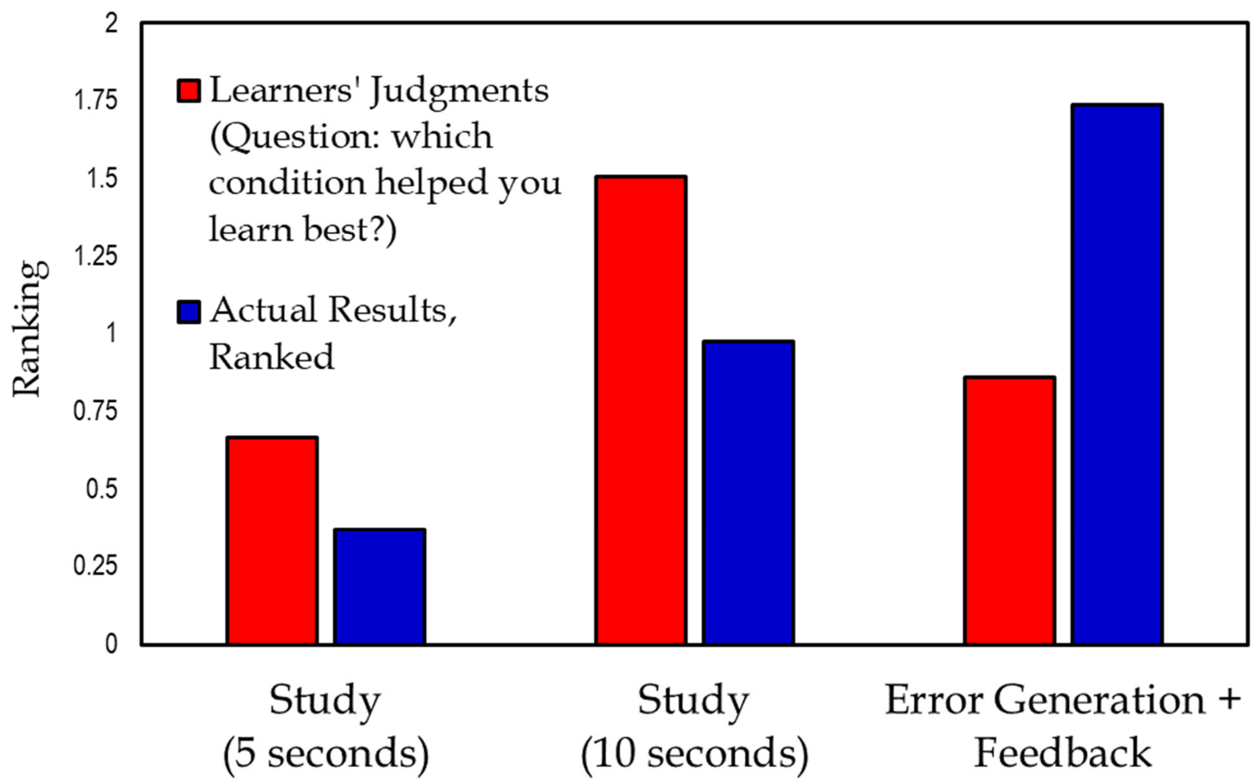

Figure 5. Effects of *studying* versus *error generation* on learners' beliefs and actual learning. Participants learned English word pairs via three methods: study a given pair for (a) 5 seconds or (b) 10 seconds, or (c) attempt to guess for 5 seconds, followed by 5 seconds of correct answer feedback (*error generation + feedback*). Participants ranked the 5-second study condition as the most effective for learning. However, as evident on a subsequent recall test, generating errors yielded, by far, the best learning (related word pair results shown). Figure adapted with permission from Springer Nature. Source: Huelser, B. J., & Metcalfe, J. (2012). Making related errors facilitates learning, but learners do not know it. *Memory & Cognition*, *40*(4), 514-527.

How learners interpret and internalize their own errors may also impact their subsequent ability to handle challenging tasks. For instance, Autin and Croizet (2012) had sixth grade students attempt easy or difficult anagram problems. The easy problems could all be solved with perfect accuracy, whereas the difficult problems were impossible to solve within the allotted period of time (thus giving students the experience of complete failure). Of the students that experienced the difficult anagram problems, half were part of a "reframing" condition that was told to consider difficulty as a normal and helpful component of the learning process (a similar approach to that taken in other research involving motivational mindsets, e.g., Oyserman, Elmore, Novin, Fisher, & Smith, 2018). After practicing, all of the students took a challenging reading comprehension test. On that test, students in the reframing condition scored an average of 18% and 30% higher, respectively, than the students that had easy and difficult problems without reframing (a result that the authors attributed to changes in intellectual self-worth and working memory capacity). Thus, without the realization that errors and failure are integral and helpful components of successful learning processes, the act of making errors can reduce motivation and decrease future performance. That conclusion heightens the importance of updating mental models of human learning to reflect the value of errors as learning opportunities.

Collectively, the findings of learning science research on the benefits of errors for retention and transfer suggest that education, training, and operational practices that accommodate or even emphasize learning from errors are justified. Some institutions and professions already feature such practices, with early adopters including the U.S. Army and their use of after-action reports, wherein mistakes are evaluated and strategies for improved scenario responses are proposed (Bjork, 2009), as well as the commercial aviation industry and their switch to non-punitive error reporting systems (Helmreich, 2000), which emphasize transparency about errors in order to facilitate learning from them. Additionally, it should also be noted that other desirable difficulties, including interleaving and retrieval practice, also often yield more errors than blocking and restudying, respectively. The fact that errors can be helpful for learning may in fact further add to the desirability of those techniques.

Principle 3: Regard Forgetting as a Facilitator of Learning

With computers, video cameras, and other man-made devices, the location where information is permanently stored, which usually takes the form of a disk or hard drive, is typically its most valuable component. What makes that location valuable is not its physical composition but what it contains: Memories in the form of electronic data. Deletion or overwriting of that data can be a substantial loss because it renders previously "saved" information unrecoverable, with the only resort being to re-record or re-input the data if possible. Similarly, many learners possess mental models wherein *forgetting*—that is, the inability to recall something that was previously recallable (Roediger, Weinstein, & Agarwal, 2010; Tulving, 1974)—is considered to be a highly undesirable outcome, an irreversible event, and even the polar opposite of the goals of successful learning and remembering (Bjork, Bjork, & MacLeod, 2006).

If the human brain functions in ways similar to computers and other man-made devices, then it would indeed be the case that forgetting is undesirable, except, perhaps, when one's goal might be to obliterate some upsetting or embarrassing memory. In the everyday functioning of human learning and memory, however, forgetting is far from always undesirable or akin to the erasure of data from a hard drive (for reviews and discussions of forgetting mechanisms see Bjork, 2003; Bjork et al., 2006; Roediger et al., 2010; Wixted, 2004). In fact, as a general operating principle, forgetting is an adaptive and beneficial function of the human learning and memory system (Bjork, 1978), and perhaps counterintuitively, forgetting can be regarded as a facilitator and even a "friend of learning" (Bjork, 2015, p. 15; see also Bjork, 2011).

A primary reason why forgetting is adaptive is because not all information warrants recall at any given point in time. A classic example involves remembering where one's car is parked or where one's hotel room is located (e.g., Bjork, 2011), wherein it is far from optimal to remember where one parked one's car yesterday, or a week ago, or what one's hotel room number was at last year's meeting of some organization. In such situations, it is inefficient to recall all previously memorized locations and then sift through them to decide which is most current. Many computers and other man-made devices, however, require exactly that. For example, a computer keyword search typically retrieves all instances of that keyword, and even in more advanced systems, a selection of the most recent matches that then requires further examination. The human brain uses a more efficient strategy: It remembers the current location, if not always perfectly, and inhibits prior, less relevant ones (Bjork & Bjork, 1988; for related evidence see Anderson & Schooler, 1991). That adaptive forgetting process, which occurs on a regular basis (except for rare cases of superior autobiographical or episodic memories, wherein the lack of forgetting can be highly distracting and undesirable; e.g., Luria, 1968; Parker, Cahill, & McGaugh, 2006), distinguishes the human learning and memory system from that of man-made devices.

Moreover, forgetting is qualitatively different in humans: Whereas the deletion or overwriting of data in a computer or video camera is generally infrequent and usually irreversible, forgetting in humans is a common process and involves losing the ability to retrieve a given memory at a given moment but not its irrevocable loss from long-term storage (i.e., from the perspective of Bjork and Bjork's (1992) NTofD, retrieval strength but not storage strength is lost). Consequently, human beings can relearn "forgotten" information with greater efficiency when needed.

It is also the case that what is accessible in human memory is volatile and cue dependent in ways that are both unique and adaptive. Thus, when there are competing memories, the most accessible memories tend to be those most associated with current situational and environmental cues. It is also the case that in the retention of competing information and skills there tends to be a shift in access towards primacy over time—that is, towards the first-learned skill or information—especially across a retention interval when the more recently learned skill or information is not being accessed. Such “regression” effects (Bjork, 2001) tend to be adaptive, overall, because the various circumstances that led to the disuse of more recently acquired skills and information are often those in which information or skills learned earlier are again relevant. That there can be such shifts from recency to primacy does not tend to be understood by learners (see Storm & Bjork, 2016).

Forgetting is not just adaptive for everyday living; it can also benefit the acquisition of knowledge and skills. In particular, many of the conditions that can be classified as desirable difficulties, including distributed practice and interleaving, yield substantial forgetting during training or practice (Bjork, 1994a; Bjork & Bjork, 2011). In fact, forgetting itself appears to be crucial to the efficacy of many desirable difficulties (for discussion see Bjork, 2011). According to the NTofD, training conditions that do not produce much forgetting during training, such as massed practice, increase retrieval strength over the short term but do not yield the corresponding changes in storage strength that are necessary to support long-term retention and transfer. Conversely, conditions that do produce forgetting during training, as evidenced by reduced retrieval strength, can yield the necessary gains in storage strength (Bjork & Bjork, 1992). As an example, crammed study of a list of facts can improve the ability to recall those facts over the short term, but yields substantial forgetting over the long term; in contrast, spaced study will yield more forgetting in the short term (i.e., across study attempts) but better memories for those facts over the long term. Other accounts of forgetting's beneficial impacts on learning include that forgetting results in the encoding of more contextual cues over time (Estes, 1955a; see also Bower, 1972); that retrieval processes which occur after forgetting has taken place require more effort and are more efficacious as a result (e.g., Pyc & Rawson, 2009); that forgetting causes learners to engage in more problem-solving activities (Jacoby, 1978); and for the case of physical tasks, that there is more "reloading" of motor programs (i.e., neural representations that underlie task execution) when forgetting has occurred (Lee & Magill, 1983).

Besides mischaracterizing the adaptive and beneficial role of forgetting, many learners are also unable to accurately estimate the amount of forgetting that occurs over time. Multiple empirical studies have demonstrated the existence of a *stability bias*—that is, the tendency to believe that the current accessibility of information in memory will remain constant over time, rather than be enhanced or attenuated due to forgetting or other processes (e.g., Kornell & Bjork, 2009; Kornell, 2011; see also Ariel, Hines, Hertzog, 2014; Koriat, Bjork, Sheffer, & Bar, 2004). That bias may stem from overconfidence, *perceptual fluency* (i.e., a sense of familiarity with the materials that one is trying to learn; e.g., Reder & Ritter, 1992; Undorf, Zimdahl, & Bernstein, 2017), or *retrieval fluency* (i.e., the ease with which information can be recalled; e.g., Benjamin & Bjork, 1996; see also Benjamin, Bjork, & Schwartz, 1998). Underestimates of forgetting can also lead learners to overestimate the efficacy of rereading, restudying, and other suboptimal study strategies, and avoid using more potent learning techniques as a result.

Overall, forgetting ranks next to the learning-versus-performance distinction as one of the most misunderstood aspects of the human learning and memory system. In human beings, forgetting occurs in a dramatically different fashion from broadly analogous processes in computers and other man-made devices, has many beneficial aspects that belie its generally negative reputation, including being a vital component of many effective learning methods, and manifests in ways that learners are often not well-calibrated to predict. As such, it is crucial that accurate mental models of the human learning and memory system classify forgetting processes as both essential and adaptive for its optimum functioning.

Principle 4: Do Not Be Led Astray by Neuromyths

Students' and instructors' mental models of human learning are susceptible to flaws other than the human-as-a-computer analogy. These models include other beliefs that might seem highly plausible, even to fairly sophisticated consumers of scientific knowledge, such as: Instruction and training should be geared toward individual "learning styles;" differences in brain hemispheric dominance dictate how effectively one is able to learn (i.e., "left-brained" vs. "right-brained"); humans typically use only 10% of their brain capacity; one can learn to become a highly efficient multitasker; brain training games yield broad improvements in cognitive capabilities, and more (Dekker, Lee, Howard-Jones, & Jolles, 2012; Herculano-Houzel, 2002; Howard-Jones, 2014; Kirschner & van Merriënboer, 2013; Simons et al., 2016; van Dijk & Lane, 2018). Each of these claims, however, can be categorized as a *neuromyth* (Crockard, 1996)—that is, an unscientific idea about how the brain works (or when discussing learning and education more specifically, an *edumyth*). None enjoy strong empirical support. In fact, there is substantial evidence to conclude that each of these aforementioned neuromyths is misleading or downright false. Yet such beliefs continue to persist, in some cases for decades.

A major reason why neuromyths are prevalent is that they are intuitively appealing. Neuromyths appear to account for various learning phenomena or convey plausible ideas about one's supposed learning capacities. For instance, some neuromyths can excuse a lack of learning or poor performance (e.g., perhaps one did not learn well in a course because it was not taught in a manner that fit their individual characteristics; or, one might simply not be "wired" to learn mathematics or some other domain). Endorsing such beliefs tends to absolve the learner of any responsibility for their own learning outcomes, or, for parents, give license to blame instructors for subpar academic performance (Pashler, McDaniel, Rohrer, & Bjork, 2009). Other neuromyths suggest latent capacities of the human learning and memory system that are highly attractive (e.g., if one could tap into the "90% of the brain that is typically left unused," then imagine what heights one could reach; or, if one learned to multi-task or used the most effective brain training games, then perhaps one might become able to acquire new knowledge and skills with far greater speed and efficiency). In some cases, believers of such neuromyths can find validation in the literature, but typically via studies that are methodologically flawed, poorly researched, rely solely on correlational evidence, were conducted by researchers with financial or other conflicts of interest, or were published in less-than-rigorous scientific journals (for discussions see Cuevas, 2015; Pashler et al., 2009; Simons et al., 2016). Such studies sometimes also receive mainstream media, online, or other press coverage, where they further contribute to the prevalence and longevity of neuromyths.

Perhaps the most pervasive of the neuromyths is that of individual "learning styles." In every country surveyed to date across at least four continents, members of the public and educators commonly endorse the claim that individuals learn most effectively when instruction is tailored toward their preferred manner of learning, be it via visual, auditory, kinesthetic, or other modes (by that account, a "visual learner" should always receive instruction via graphical presentation, an "auditory learner" should only hear instructional content, and so on). Surveys typically report 85-90% respondent agreement with the learning styles neuromyth (e.g., Dekker et al., 2012; Gleichgerrcht, Lira Luttges, Salvarezza, & Campos, 2015; Morehead et al., 2016; Newton, 2015; Pei, Howard-Jones, Zhang, Liu, & Jin, 2015; Rato, Abreu, Castro-Caldas, 2013; Scott, 2010; Tardif, Doudin, & Meylan, 2015). In alignment with such beliefs, the mandatory administration of learning styles inventories, the use of learning styles workshops and consulting services, and attempts to modify instruction to reflect putative learning styles have become increasingly popular (Pashler et al., 2009). Contrary to popular opinion, however, in-depth reviews of the research on learning styles—wherein the "gold standard" of evidence includes studies in which the method of instruction is experimentally manipulated to match or not match students' preferred learning styles, and the outcomes objectively measured—have found no compelling evidence to support their utility (e.g., Cuevas, 2015; Pashler et al., 2009; see also Coffield, Moseley, Hall, & Ecclestone, 2004; Kampwirth & Bates, 1980; Stahl, 1999; Willingham, Hughes, & Dobolyi, 2015). In fact, most empirical studies have shown zero benefit of matching instruction to learning styles (e.g., Choi et al., 2009; Cook, Thompson, Thomas, & Thomas, 2009; Massa & Mayer, 2006), and in some cases, researchers have concluded that specific instructional techniques (e.g., the use of effective study strategies) benefit the vast majority of learners regardless of their preferred learning style (e.g., Constantinidou & Baker, 2002; Cuevas & Dawson, 2018; Husmann & O'Loughlin, 2019).

Despite the lack of evidence for learning styles as a useful educational concept, learning preferences among individuals (such as differences in one's personal appreciation for a given method of instruction, content domain, or learning technique) most assuredly exist (Brown et al., 2014), along with differences in learning aptitude, background knowledge, and more. Tailoring instruction to ability levels, such as using practice problems that are appropriate in difficulty for learners' training or knowledge levels at a given point in time, can have benefits (for discussions see Brown et al., 2014; Pashler et al., 2009; Willingham et al., 2015). Tailoring instruction to individual learning styles or preferences, however, is usually not beneficial (Kirschner & van Merriënboer, 2013). Moreover, unlike learning styles-based instruction, many of the learning techniques that qualify as desirable difficulties—including distributed practice, interleaving, and retrieval practice—have been established to be broadly effective, including for different types of materials (for reviews see Cepeda et al., 2006; Pan & Rickard, 2018; Rawson & Dunlosky, 2011), for learners of diverse ages, (e.g., Maddox & Balota, 2015; Meyer & Logan, 2013; Vlach, Sandhofer, & Kornell, 2008), across different levels of memory ability (e.g., Pan, Pashler, et al., 2015; Sana, Yan, Kim, Bjork, & Bjork, 2018), and more. These evidence-based learning techniques enjoy substantial empirical support and stand a much greater chance of enhancing learning for different learners and across a variety of circumstances.

In summary, accurate mental models of human learning should incorporate, as a basic principle, the fact that various popular and seductive neuromyths do not reflect the actual functioning of the human learning and memory system. More broadly, the prevalence of neuromyths further illustrates the gulf between learners' mental models of learning and reality: Even when human beings accept that they learn in ways that differ from that of computers or other man-made devices, they can fall prey to inaccurate, even fanciful, ideas about how the human learning and memory system operates.

Concluding Comments

In this chapter we have endeavored to say both why having an accurate mental model of how human beings learn is critical to optimizing instruction and self-regulated learning and why learners are prone to having faulty models. We submit that learners should adopt a mental model that includes four basic operating principles: (i) learning and performance are not synonymous;

(ii) introducing difficulties into the learning process can, in certain situations, yield more durable and flexible learning over the long term; (iii) forgetting is an essential and adaptive process that benefits learning; and (iv) neuromyths and other unsupported claims about the human learning and memory system can lead learners astray.

We subtitled this chapter “towards an owner’s manual,” rather than “an owner’s manual,” because there remains much to be learned. It is one thing, for example, to say that interleaved practice can enhance long-term retention and transfer, but it is another to say how the benefits of interleaving, if any, depend on the relatedness and “chunk size” of what is being interleaved, on the level of prior learning that a given learner brings to the instruction or practice that is required in a given domain, and so forth. Similar considerations apply with respect to the other “operating principles” we have discussed. Learning science research promises answers to these and further questions in the years to come.

There are motivational issues as well. Even if learners are convinced in a kind of academic way that difficulties can be desirable, that making errors can enhance learning, that forgetting can enhance learning, and that a high level of current performance may be a product of current conditions and constraints rather than actual learning, making efforts to actually incorporate procedures and processes that create a sense of difficulty, increase errors, and reduce current performance is a lot to ask, especially if such procedures and practices go against one’s habits and how one was taught. From that standpoint, becoming a maximally effective learner—or teacher—is no easy task.

As we argued at the beginning of this chapter, though, knowing how to learn is the ultimate survival tool in our “ever more complex and rapidly changing world,” so the rewards of incorporating the operating principles we have discussed are considerable. With improved mental models, learners stand to more fully capitalize on the impressive capabilities and potential of the human learning and memory system.

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