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REVIEW ARTICLE

Eight Ways to Promote Generative Learning

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Abstract Generative learning involves actively making sense of to-be-learned information by mentally reorganizing and integrating it with one's prior knowledge, thereby enabling learners to apply what they have learned to new situations. In this article, we present eight learning strategies intended to promote generative learning: summarizing, mapping, drawing, imagining, self-testing, self-explaining, teaching, and enacting. First, we provide an overview of generative learning theory, grounded in Wittrock's (1974) generative model of comprehension and reflected in more recent frameworks of active learning, such as Mayer's (2014) select-organize-integrate (SOI) framework. Next, for each of the eight generative learning strategies, we provide a description, review exemplary research studies, discuss potential boundary conditions, and provide practical recommendations for implementation. Finally, we discuss the implications of generative learning for the science of learning, and we suggest directions for further research.

Keywords Generative learning · Learning strategies · Comprehension · Transfer

Learning is a generative activity. This statement is based on the idea that learning involves actively constructing meaning from to-be-learned information by mentally reorganizing it and integrating it with one's existing knowledge (Fiorella and Mayer 2015; Wittrock 1974). As Wittrock (1989) put it, "…the mind… is not a passive consumer of information," rather, "…it actively constructs its own interpretations of information and draws inferences on them" (p. 348). This form of active cognitive processing enables learners to develop an understanding of the material that they can apply in new situations. In short, generative learning is the process of transforming incoming information (e.g., words and pictures) into usable knowledge (e.g., mental models, schemas). As such, generative learning depends not only on how information is presented to learners (i.e., instructional methods) but on how learners try to make sense of it

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(i.e., learning strategies). Although much research focuses on instructional methods—that is, what the instructor can do to promote learning (e.g., Mayer 2014; Merrill 2012; Sweller et al. 2011)—in this article, we focus on a growing area of research interested in what the learner can do to foster generative learning—or what we refer to as *generative learning strategies.*

Generative Learning Theory

Generative learning theory has its roots in Bartlett (1932) view of learning as an act of construction, in which people invest *effort after meaning* by integrating new experiences with their existing knowledge structures or schemas. Similarly, it relates to Piaget (1926) theory of cognitive development as a process of assimilating and accommodating information to existing schemas. Generative learning theory is also in line with Gestalt psychologists' (Katona 1940; Wertheimer 1959) distinction between learning by memorizing (or *reproductive thinking*) and learning by understanding (or *productive thinking*). Finally, generative learning theory is inspired by the cognitive revolution, including research on information processing models of memory (Atkinson and Shiffrin 1968), particularly as applied to text comprehension (Bransford and Franks 1971; Kintsch and van Dijk 1978) and the organized nature of knowledge (Ausubel 1960). These early contributions all converge on the idea that human learning and memory are constructive and that learning for understanding involves building meaningful knowledge structures that can be applied to new situations.

Wittrock (1974, 1989) pioneered efforts to apply these early insights toward a theory of meaningful learning relevant to education. Wittrock's generative model of learning is based on the premise that learners "generate perceptions and meanings that are consistent with their prior knowledge" (Wittrock 1974, p. 88) and that "learning with understanding involves the process of generating and transferring meaning for stimuli and events from one's background, attitudes, abilities, and experiences" (p. 93). According to Wittrock's (1989) model, meaningful learning consists of four main components: generation, motivation, attention, and memory. *Generation* refers to the connections a learner builds between the different elements of to-be-learned material (i.e., internal connections) and between the to-be-learned material and learner's existing knowledge (i.e., external connections); *motivation* refers to a learner's willingness to invest effort toward making sense of the material; *attention* refers to directing generative processes toward the relevant incoming material and stored knowledge; and *memory* refers to the learner's prior knowledge, experiences, and beliefs. By emphasizing the role of learners as active sense-makers, Wittrock's model provided the science of learning with an influential and educationally relevant theory of meaningful learning, and it provided the science of instruction with testable predictions concerning instructional methods and learning strategies aimed at promoting student understanding (Fiorella and Mayer 2015; King 1994; Mayer 2014; Mayer and Wittrock 1996, 2006; Novak 2010; Sweller et al. 2011; Weinstein and Mayer 1986; Webb 1982; Wittrock 1991, 1992).

The SOI Model of Generative Learning

Wittrock's model of generative learning is closely tied to (Mayer 2009, 2011, 2014) select-organize-integrate (SOI) model—a subcomponent of the cognitive theory of multimedia learning (Mayer 2009, 2014) and similar to Kiewra's (2005) select, organize, associate, and regulate (SOAR) framework. According to the SOI model, meaningful learning involves three primary cognitive processes and their interactions with three primary memory stores, as shown in Fig. 1. First, learners must *select* the most relevant incoming sensory information (such as words or graphics)—briefly held as an exact copy in sensory memory—for further conscious processing in working memory. Next, learners must *organize* the selected information into a coherent mental representation in working memory by building relevant connections based on the material's underlying structure (such as enumeration, process, or hierarchy). Finally, learners must *integrate* the new representation constructed in working memory with relevant knowledge structures stored in long-term memory (such as schemas, categories, or principles). The processes of organizing and integrating are referred to as *generative processing*, which involves building a new mental representation based on one's relevant existing knowledge. Taken together, the cognitive processes of selecting, organizing, and integrating relate closely to Wittrock's conceptions of attention (selecting), building internal connections (organizing), and building external connections (integrating). The SOI model has also influenced the development of SOAR study system of Kiewra (2005) and Jairam et al. (2014), which includes the cognitive processes of selecting, organizing, and associating (similar to integrating), and further includes the metacognitive process of *regulating*.

The SOI model also recognizes the important role of metacognitive and motivational processes in generative learning (Mayer 2014). Metacognition involves the awareness and control of one's own cognitive processes—such as knowing which information to select, what kind of knowledge structure to build, and which prior knowledge to activate during learning. Thus, generative learning depends on the ability to accurately evaluate one's own understanding of the material and to select appropriate learning strategies that prime selecting, organizing, and integrating. Yet, even if learners possess strong metacognitive skills, they still must be motivated to initiate and maintain generative processing—that is, they must be willing to invest cognitive effort toward making sense of the material during learning. Motivation can be influenced by a myriad of factors, such as the learner's interests, goals, beliefs, and attributions about their own learning. Taken together, metacognition and motivation are the power source of generative learning—serving to initiate, maintain, monitor, and direct appropriate cognitive processing (i.e., selecting, organizing, and integrating) during learning.

The SOI model of generative learning is also closely related to Chi's interactive-constructive-active-passive (ICAP) framework (Chi 2009; Chi and Wylie 2014). The ICAP framework distinguishes between four modes of cognitive engagement based on students' overt

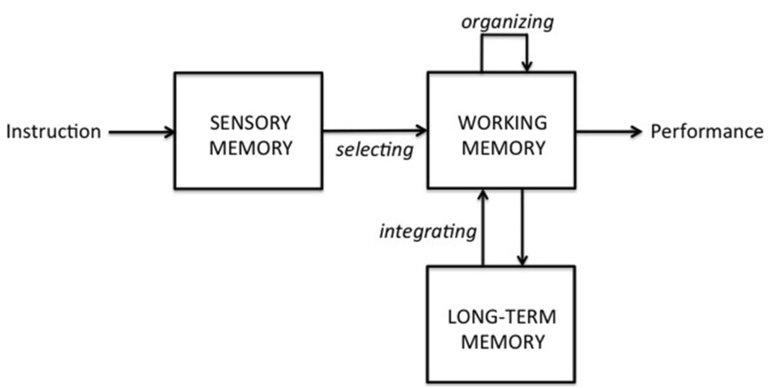

Fig. 1 The select-organize-integrate (SOI) model of generative learning

behaviors. The *passive* mode takes place when learners receive information without engaging in any overt behavior related to learning; the *active* mode takes place when learners engage in some form of overt action that does not go beyond the information presented (e.g., writing verbatim notes, underlining); the *constructive* mode occurs when learners engage in overt behaviors that involve generating ideas that go beyond the to-be-learned information (e.g., self-explaining); and the *interactive* mode takes place when learners engage in dialogue that involves constructive behavior (e.g., asking and answering questions with a peer, defending an argument). The primary prediction of this framework is that as students become more cognitively engaged with the material (i.e., as students move from the passive to active to constructive to interactive mode), meaningful learning outcomes (such as comprehension and transfer) should be enhanced. Thus, the ICAP framework is consistent with the SOI framework of generative learning, with generative processing (which involves organizing and integrating the incoming information) corresponding to constructive and interactive modes of cognitive engagement, whereas passive and active modes of engagement do not involve generative processing.

Wittrock's early conception of generative learning and Mayer's SOI framework—as well as other similar frameworks of active learning (e.g., Chi and Wylie 2014; Kiewra 2005; Kintsch 1998—have resulted in a large body of empirical research investigating ways in which teachers and students can foster meaningful learning (Dunlosky et al. 2013; Fiorella and Mayer 2015; Grabowski 2004). In this section, we summarize empirical evidence for eight learning strategies shown to promote generative learning: summarizing, mapping, drawing, imagining, self-testing, self-explaining, teaching, and enacting. These strategies are considered generative because they aim to motivate learners to actively make sense of to-be-learned information during learning—by selecting the most relevant information, organizing it into a coherent mental representation, and integrating it with their existing knowledge. Our list of eight strategies is not intended to represent an exhaustive account of effective learning strategies; rather, it aims to represent learning strategies that are well-studied (i.e., many empirical research studies have investigated their effectiveness), that are well-supported (i.e., the strategies are consistently shown to improve student learning), and that target generative learning (i.e., meaningful learning outcomes such as comprehension and transfer rather than rote learning outcomes such as recall). Previous reviews of learning strategies (Dembo and Junge 2005; Dunlosky et al. 2013; Nist and Holschuh 2000; Pressley et al. 1995; Weinstein and Mayer 1986) are often more broad to include strategies that are not effective or that target rote learning (e.g., rereading, highlighting, underlining) or that deal with other aspects of learning or studying (e.g., scheduling practice, time management, reducing anxiety). The current article aims to provide a focused synthesis of eight learning strategies, each intended to promote generative learning and to provide specific practical recommendations for implementing each of the strategies based on the available research evidence.

In the following eight subsections, we define a generative learning strategy, describe how it relates to generative learning theory, summarize exemplary research studies demonstrating the strategy's effectiveness, discuss potential boundary conditions, and provide practical recommendations for implementation. We then summarize the large empirical research base across each of the strategies, discuss how each of the strategies can be applied effectively within different learning contexts (e.g., learning from lectures or textbooks or while studying), and suggest some future directions for advancing the study of generative learning.

Learning by Summarizing

Summarizing involves concisely stating the main ideas from a lesson in one's own words. In line with generative learning theory, an effective summary goes beyond copying words or phrases verbatim from the lesson; rather, it involves selecting the most relevant information from the lesson, organizing it into a coherent structure such as an outline, and integrating it with students' prior knowledge such as adding new material. In other words, summaries that prime generative learning include learners' own interpretations of the important information, based on their existing knowledge. In much of the research on learning by summarizing, students are asked to generate short written summaries while studying text passages (e.g., Annis 1985); however, research has also tested the effects of summarizing following learning (a form of self-testing; e.g., Coleman et al. 1997), taking summary notes during a lecture (a form of note taking; e.g., Peper and Mayer 1986), and generating oral summaries (similar to teaching; e.g., Ross and Kirby 1976).

A classic study by Doctorow et al. (1978) demonstrates the potential benefits of generating summaries for reading comprehension. In the study, middle school students read a narrative text passage; some students were asked to read the passage normally without instructions to use a learning strategy (control group), whereas other students were asked to write a one-sentence summary in a blank space above each paragraph (summary group). The summary group greatly outperformed the control group on a subsequent comprehension test, and this effect was especially strong for students with low ability ($d=1.58$), suggesting that summarizing while reading is more effective than reading without using a learning strategy. A study by Bretzing and Kulhavy (1979) found that summarizing is also more effective than asking students to take verbatim notes while learning from a text. Taken together, these early studies suggest that providing students with instructions to summarize helps them actively select and interpret the main ideas from a text (by putting the main ideas into their own words), resulting in better comprehension. More recent research on summarizing indicates that writing summaries may also provide students with metacognitive benefits, helping them better assess their own level of comprehension (Anderson and Thiede 2008; Thiede and Anderson 2003).

Although summarizing can be effective in some situations, other research studies indicate a few important boundary conditions. For example, summarizing appears to be most effective when the to-be-learned material consists of short expository texts that are not highly spatial in nature (e.g., Leopold and Leutner 2012; Wittrock and Alesandrini 1990). When the material is highly spatial, such as in physics or chemistry, other generative learning strategies are likely more appropriate (e.g., imagining, mapping, drawing, or enacting; see Leopold and Leutner 2012). Not surprisingly, the effectiveness of summarizing (as well as other generative learning strategies) also depends on the ability of students to generate quality summaries on their own. Some studies suggest that students may struggle to generate quality summaries when they are provided with only minimal instructions and without training in how to summarize (Bednall and Kehoe 2011; Garner 1982). Thus, one limitation of summarizing is that it may require extensive training in how to select main ideas and create quality summaries that use students' own words (e.g., Bean and Steenwyk 1984; Friend 2001; King et al. 1984; Selcuk et al. 2011; Taylor and Beach 1984). For example, a training study by Bean and Steenwyk (1984) found benefits of providing middle schoolers with approximately 6 h of summarizing instruction over the course of 5 weeks.

Practical Recommendations

The existing research evidence suggests that summarizing can be an effective strategy when learning from short text passages and while taking notes during lecture-based instruction but that some students (particularly younger learners) may need extensive training in how to summarize effectively (i.e., selecting main ideas and stating them in their own words). Effective training programs typically involve some form of instructor modeling, followed by guided practice with feedback; however, research is needed to pinpoint how much training is needed across different grade levels. There is also some evidence that the nature of the to-be-learned material plays an important role—that is, summarizing may be most effective for restating relatively simple ideas or concepts or for material that is not highly spatial (such as learning from narrative texts or within the social sciences or humanities) but may not be as appropriate for complex spatial concepts (such as in physics or chemistry). It may also be that summarizing is appropriate for some aspects of a lesson, whereas other generative learning strategies should be used to represent other aspects of the lesson. Further research is needed to understand how summarizing may be used in conjunction with other learning strategies.

Learning by Mapping

Learning by mapping refers to a collection of techniques in which a learner converts printed or spoken text into a spatial arrangement of words and links among them, including concept maps, knowledge maps, and graphic organizers. A concept map is a network in which the nodes (usually enclosed by an oval or rectangle) are words representing key concepts and the links are relations between them (usually represented as lines with a verbal description of the relation printed above the line). A knowledge map is a particular kind of concept map in which the links are restricted to a set of basic predefined relations such as *part of*, *type of*, *leads to*, and *characteristic of*. A graphic organizer is an even more specialized type of concept map in which the key concepts are arranged within a particular predefined rhetorical structure, such as a matrix for a compare-and-contrast structure, a flow chart for a cause-and-effect process, and a hierarchy for classification structure. For example, in mapping the foregoing three sentences, a learner could begin by creating a hierarchy with the topmost node containing *type of mapping* with three nodes in the row under it containing *concept map*, *knowledge map*, and *graphic organizer*, along with links labeled *type of*. In line with generative learning theory, the act of creating or completing a concept map, knowledge map, or graphic organizer encourages learners to select relevant information to use as the nodes, to organize them into a coherent structure as specified in the links, and to integrate the incoming material with relevant prior knowledge by determining the overall structure of the material. In short, generative learning is fostered when learners translate from linear text to spatially arranged text that highlights the structure of the lesson.

In an exemplary concept mapping study, Chularut and DeBacker (2004) asked high school and college students to read a series of text lessons across five sessions, either using their normal study technique (control group) or being asked to create concept maps for each lesson based on previous training and guided by feedback from the instructor (mapping group). Results indicated that the mapping group outperformed the control group on a subsequent achievement test consisting of comprehension and transfer items. Further, this effect was stronger for students with high English proficiency compared to students with low English proficiency. Overall, this research suggests that students may need pretraining in how to create concept maps prior to learning and guidance in creating them during learning.

In a pioneering knowledge mapping study, Holley et al. (1979) asked college students to read a geology lesson and either create a knowledge map based on 5 h of pretraining (mapping group) or take notes normally (control group). On subsequent recall and recognition tests of the main ideas of the lesson given 5 days later, the mapping group outperformed the control group, with the strongest effects shown for students with lower grade point average (GPA). Thus, two important boundary conditions of knowledge mapping appear to be that extensive pretraining is required and the effects are strongest for students with lower academic records.

In a recent study on graphic organizers, Ponce and Mayer (2014) asked college students to read an onscreen text about steamboats on the left side of the screen while filling in an onscreen matrix on the right side of the screen (mapping group) or while taking convention notes in a box on the right side of the screen (control group). Results indicated that the mapping group outperformed the control group on a subsequent set of tests that involved writing a summary of the passage and completing a modified cloze test, yielding a high effect size (d=1.10).

Overall, there is consistent evidence across all three varieties of mapping strategies that learning by mapping can be a highly effective learning strategy. In a review, Nesbit and Adelsope (2006) reported an average weighted effect size of d=0.87 favoring self-generated concept maps. In short, students tend to learn better when they are asked to translate text into a spatial representation using the key concepts. In applying mapping strategies in academic settings, it may be worthwhile to provide adequate pretraining before learning and guidance during learning in how to construct appropriate spatial representations. Mapping strategies may be time-consuming and somewhat tedious for some learners, so it may be useful to reduce the demands of the task by asking learners to fill in partially completed maps.

Practical Recommendations

We assess that there is strong evidence for the utility of mapping strategies in improving student learning from expository text passages. However, two major obstacles to implementation are that (1) students may need training in how to create useful maps when they lack experience and (2) students may lose interest in constructing maps when the map-building process is tedious and time-consuming. Research is needed in how to effectively simplify and scaffold the map-building process, perhaps through automated online systems for creating online concept maps (Juarez Collazo et al. 2015) or training in using a small collection of ready-made templates (Hilbert and Renkl 2009).

Learning by Drawing

In learning by drawing, learners create a drawing—either by hand or using computer tools—to depict the content of a lesson (Leutner and Schmeck 2014; Van Meter and Garner 2005; Van Meter 2013). For example, while reading a lesson on how an electric battery works, a learner could draw a picture for each section, as in an early study by Alesandrini (1981). According to generative learning theory, the act of translating from text to a pictorial representation prompts the learner to select the relevant information from the text, show its organization spatially in a drawing, and use prior knowledge to clarify the meaning of the text and its relation to the drawing. However, it is possible that the act of drawing could create extraneous processing if the learner has to focus on the tedious mechanics of drawing rather than the content of the lesson. The potential for extraneous processing can be minimized by providing instructional supports for drawing before or during learning, such as showing how to draw key elements (Leutner and Schmeck 2014).

In an exemplary study, Schwamborn et al. (2010) asked ninth graders to read a short text passage on the chemistry of washing clothes with soap and water, either with or without instructions to make a drawing. To minimize cognitive load associated with the act of drawing, students in the drawing group drew on a sheet in which the background was predrawn and key elements were already drawn in the margins for easy copying. On a subsequent transfer test, the drawing group outperformed the control group, yielding a large effect size (d=0.81). This study is an example of what the authors call the *generative drawing effect*—that is, people learn better from a scientific text when they are provided with support in how to create a drawing that depicts the material in the text.

Overall, there is a substantial body of evidence supporting the effectiveness of learning by drawing, particularly when the mechanics of drawing does not require excessive attention. Importantly, the benefits of drawing have been found with elementary school students, high school students, and college students. Concerning boundary conditions, the effectiveness of drawing tends to be greater when students receive explicit pretraining in how to draw (Gobert and Clement 1999), when they receive more detailed guidance on which elements to include in the drawing Alesandrini (1981), when they get support by receiving partially drawn illustrations Schwamborn et al. (2010), or when they are asked subsequently to compare their self-generated drawings with author-provided drawings (Van Meter 2001; Van Meter et al. 2006). Thus, learning by drawing is most effective when students have a clear specification of what to draw and do not experience distracting mechanical problems in producing the drawings.

Practical Recommendations

We assess that there is preliminary evidence for the effectiveness of drawing as a learning strategy, but instructors need to be careful in the way that drawing is implemented. First, based on the current state of the research base, we recommend that students be given very specific directions concerning what to draw, including the parts that should be included. Second, we recommend that the demands of the mechanics of drawing be minimized, perhaps by having a predrawn background and simple elements in the margins that can be easily copied. Third, in some cases, students may need pretraining and practice in how to produce effective drawings. In conclusion, Leutner and Schmeck (2014, p. 433) noted in a recent review of learning by drawing: "An important logistical issue for instructional designers when using the drawing strategy is to create a form of drawing activity that minimizes the creation of extraneous cognitive load caused by the mechanics of drawing, by providing appropriate support for drawing."

Learning by Imagining

In learning by imagining, learners create mental images that depict the content of a lesson. For example, in a text lesson on how the human respiratory system works, students could be asked to mentally construct an image of the content of each paragraph, as in a recent study by Leopold and Mayer (2015). Research on imagining as a learning strategy includes imagining procedural steps such as using a spreadsheet (Cooper et al. 2001) or using a bus schedule

(Leahy and Sweller 2005, 2008), as well as imagining the structure and processes described in reading scientific texts about how a biological system works (Leutner et al. 2009; Leopold and Mayer 2015).

According to generative learning theory, the act of translating from text to a mental image prompts the learner to select the relevant information from the text, show its organization spatially in the mental image, and use prior knowledge to clarify the meaning of the text and its relation to the image. Unlike drawing, described in the previous section, there is no danger of distraction caused by the mechanics of drawing. However, it is possible that the act of imagining could create extraneous processing if the learner is confused about what to imagine, so learners may need pretraining or specific directions for imagining.

In a recent study, Leopold and Mayer (2015) asked college students to read an online nine-paragraph lesson on how the human respiratory system works, with one paragraph presented on the screen at a time. Some learners (imagining group) received pretraining in how to form mental images for scientific text, and for each paragraph, they were given a focused prompt to form a mental image containing specific parts of the respiratory system in a blank space to the right of the text. The imagining group scored better on a subsequent transfer test than a group that simply read the paragraphs (control group), yielding large effect sizes (exp. 1 $d=1.30$; exp. 2 $d=0.86$). Unlike research on drawing, providing an author-drawn illustration for each paragraph after students formed an image tended to diminish the imagining effect, presumably because this took away the incentive to form a useful mental image.

Concerning boundary conditions, imagining appears to be more effective for students with high rather than low prior knowledge (Cooper et al. 2001; Ginns et al. 2003; Leahy and Sweller 2005) perhaps because imagining is too cognitively demanding for low-knowledge learners. In applying imagining to everyday learning tasks, it is useful to remember that short-term studies have focused mainly on imagining as an aid to learning about procedures and how scientific systems work. Learning by imagining is likely to be most effective when students have had practice in how to engage in productive imagining, when they are given specific prompts for what to imagine, and when they are somewhat familiar with the domain.

Practical Recommendations

We assess that there is promising preliminary evidence for learning by imagining as a learning strategy, but instructors should be sensitive to potential difficulties that students can have in generating useful mental images. First, based on the current state of the research literature, we recommend limiting imagining to learners who have sufficient prior knowledge and using different strategies for beginners. Similarly, imagination should not be used when the material is overly complex for the learner. Second, we recommend that instructors provide very specific prompts concerning what to imaging including explicitly naming the components to be included. Third, learners should be given pretraining and practice in how to form useful mental images from expository text. In short, imagination strategies require more commitment from the learner because there is no behavioral activity required.

Learning by Self-Testing

Self-testing—also referred to as the *testing effect* or *retrieval-based learning*—involves answering practice questions about previously learned material. In line with generative learning theory, self-testing serves to selectively activate and retrieve students' most relevant knowledge, organize the material by strengthening existing connections between elements of the previously learned information, and integrate the material by building new connections between previously learned information and with other relevant prior knowledge. Consequently, taking practice tests leads to more persistent learning outcomes than merely restudying the material, which does not involve deep cognitive processing. The benefits of self-testing are grounded in basic memory research (e.g., Allen et al. 1969), often involving memory for word lists or paired associates. However, in recent years, researchers have investigated the testing effect with more meaningful learning materials such as prose passages (e.g., Roediger and Karpicke 2006), more meaningful learning outcomes such as transfer (e.g., Butler 2010; Johnson and Mayer 2009), and more diverse student populations such as young children (e.g., Karpicke et al. 2014).

In an exemplary study by Roediger and Karpicke (2006), students read short text passages about the sun or about sea otters and then either took a practice free recall test on the passage (study-test group) or reread the passage (study-study group). Results indicated that the study-study group outperformed the study-test group when a final recall test was administered immediately; however, the study-test group outperformed the study-study group when the final recall test was administered following a 2-day or 3-week delay. Interestingly, the study-study group also reported greater judgments of learning than the study-test group, despite worse long-term recall. Overall, this study and many others demonstrate that self-testing promotes long-term retention of meaningful learning materials, even though students may not realize its learning benefits (Karpicke and Grimaldi 2012). Indeed, other research suggests that, despite its benefits, many students do not choose to use self-testing when studying for courses and instead rely on suboptimal strategies such as rereading Karpicke et al. (2009).

Many subsequent studies have investigated potential moderators or boundary conditions of the testing effect. For example, there is evidence that self-testing is most effective when it is followed by corrective feedback (e.g., Kang et al. 2007), when students test themselves repeatedly (e.g., Butler 2010; Roediger and Karpicke 2006, and when there is a relatively close match between the content and format of the practice test and that of the final test (e.g., McDaniel et al. 2007, 2012).

Although a few recent studies have also questioned the applicability of the testing effect to more complex problem-solving tasks (i.e., materials high in element interactivity; e.g., Leahy et al. 2015; Van Gog and Kester 2012; Van Gog et al. 2015), other studies report positive effects of self-testing with complex learning materials (e.g., Darabi et al. 2007; see Rowland 2014 for a recent meta-analysis). Whereas some researchers have concluded that the testing effect does not apply to complex materials (Van Gog and Sweller 2015), others have argued that this conclusion is not warranted (Karpicke and Aue 2015; Rawson 2015) and cite existing evidence for the benefits of testing beyond basic factual information (e.g., Carpenter 2012; Karpicke 2012). This recent dissention surrounding the testing effect may be at least in part due to ambiguous and inconsistent conceptions of what constitutes "complex" learning materials. Overall, the research evidence is clear that self-testing is a highly effective learning strategy within many contexts; however, researchers need to develop clearer and more consistent methods for classifying learning materials by their degree of complexity and for classifying learning outcomes as assessing transfer. Such research should help pinpoint any potential boundary conditions that may be associated with the testing effect regarding types of learning materials and types of learning outcomes.

Practical Recommendations

Self-testing is a highly versatile learning strategy that can be applied across domains, grade levels, and studying contexts. It does not appear to require extensive training (unlike some strategies such as summarizing), yet the research evidence suggests that practice testing should be paired with immediate feedback to correct errors or misconceptions. Practice testing is also most effective when it occurs frequently and repeatedly over time. Self-testing can be effective for retaining basic factual information as well as more complex conceptual knowledge that requires inference-making—in general, it will be most effective when the retrieval activity (i.e., the format and type of practice test) closely matches the final testing event. Self-testing is somewhat unique because many of the other generative strategies can be used as opportunities for practice testing, assuming that they occur after initial learning and without the learning materials available—such as summarizing, creating a concept map, or self-explaining following learning. Thus, self-testing may be particularly useful as a study aid after initial exposure to the lesson. Further research is needed to examine how different forms of retrieval practice influence different types of learning outcomes. Overall, although self-testing does not appear to require explicit training, students may need to be taught the value of using practice testing as a learning strategy as well as the importance of repeated practice testing, compared to the use of much more common (but less effective) strategies such as rereading.

Learning by Self-Explaining

Self-explaining involves explaining the content of a lesson to oneself during learning. For example, in reading a text section on how the heart works, a student could give a running oral account of his or her efforts to understand the material, focusing on any inferences that need to be made, any points that need to be clarified, and any possible inconsistencies. In line with generative learning theory, self-explaining is most effective when students select the most important information from the lesson and restate it in their own words (similar to summarizing), generate inferences to organize the material into a coherent mental model, and integrate the material with their prior knowledge by searching for consistencies and inconsistencies between the newly presented material and their existing mental models. Learning by self-explaining is supported by a large empirical research base, which spans across subject areas, lesson formats, and age levels (e.g., Fonseca and Chi 2011; Wylie and Chi 2014). It is perhaps most often used to support learning and problem solving in math and science, such as when learning from worked examples (e.g., Renkl et al. 1998; Renkl 2014) or studying scientific texts (e.g., Chi 2000).

Classic research by Chi and colleagues (Chi et al. 1989, 1994) demonstrates the benefits of self-explaining during learning. In an initial correlational study (Chi et al. 1989), college students were asked to think aloud as they studied a physics lesson containing worked examples of problems related to the laws of motion. Students who generated more self-explanations during learning—generated inferences and reflected on their understanding of the material—performed better on a subsequent problem-solving test than students who generated fewer self-explanations during learning. In a later experimental study, Chi et al. (1994) asked eight graders to study a text about the human circulatory system. Some students were prompted to self-explain after each sentence they read (self-explain group), whereas other students read the text twice (control group). Results indicated that they self-explain group outperformed the control group on a subsequent test items intended to measure deep understanding. Overall, this study suggests that prompting students to generate self-explanations during learning fosters generative processing, thereby resulting in meaningful learning outcomes.

Many studies have documented the benefits of prompting students to self-explain during learning (see Wylie and Chi 2014 for a recent review). This research—similarly to research on other generative learning strategies—is based on the idea that students often do not employ effective learning strategies spontaneously. For example, even highly effective instructional methods such as learning from worked examples ultimately depend on whether students actively explain solution steps to themselves (e.g., Renkl et al. 1998). Recently, self-explanation prompts have been effectively incorporated within computer-based learning environments such learning from educational games (e.g., Mayer and Johnson 2010), intelligent tutoring systems (e.g., Aleven and Koedinger. 2002), and instructional animations (e.g., de Koning et al. 2011). Of course, the effectiveness of self-explanation prompting depends on the extent to which students are able to generate quality explanations on their own. Thus, in some cases, students may need more focused or guided forms of prompting (e.g., Johnson and Mayer 2010) or even explicit training (e.g., Kurby et al. 2012) in how to self-explain effectively.

Practical Recommendations

The research evidence clearly indicates strong and consistent support for learning by self-explaining. This strategy should be primarily geared toward helping students understand complex conceptual material, such as in math and science. This is because self-explaining is intended to help students reflect on their own understanding of the material, recognize misconceptions, and repair faulty mental models. Self-explaining is particularly useful when learning from complex diagrams or when studying examples. As such, self-explaining is most suitable for students to use during learning, such as repeatedly asking oneself, “does this make sense?” while reading a textbook chapter, or studying diagrams or examples. Many students do not self-explain spontaneously while learning and may need some explicit prompting and guidance in how to generate quality explanations that involve inference-making and elaboration.

Learning by Teaching

Learning by teaching involves explaining to-be-learned material with the goal of helping others learn. Thus, teaching is similar to but distinct from learning by self-explaining. In line with generative learning theory, learning by teaching involves selecting the most relevant information to include in one’s explanation, organizing the material into a coherent structure that can be understood by others, and elaborating on the material by incorporating one’s existing knowledge. Whereas the self-explaining literature contains a relatively large and systematic body of empirical research, the learning by teaching literature is more diverse—that is, the use of teaching as a learning strategy has been implemented in many different ways. For example, the idea that teaching promotes learning is embedded in common classroom practices such as peer tutoring (e.g., Palincsar and Brown 1984), cooperative learning (e.g., Slavin 1983), and small group discussions (e.g., Webb 1982). More recently, researchers have investigated the learning benefits of teaching computer-based pedagogical agents (e.g., Biswas et al. 2005). Generally, research suggests that teaching can be an effective way to learn

(Roscoe and Chi 2007); however, fewer studies have systematically isolated the effects of student teaching on learning (e.g., Annis 1983; Coleman et al. 1997; Fiorella and Mayer 2013, 2014; Roscoe and Chi 2008).

Learning by teaching is also unique because—in addition to the act of explaining—it involves other factors that can contribute to learning, such as preparing to teach and interacting with others (e.g., Bargh and Schul 1980; Fiorella and Mayer 2013, 2014; Muis et al. 2015a; Roscoe and Chi 2008). Recent research by Fiorella and Mayer (2013, 2014) aimed to systematically examine the relative and interdependent effects of teaching expectancy (i.e., preparing to teach) and actually teaching (i.e., explaining to others). In a series of experiments, college students learned about how the Doppler effect works with instructions that they would later be tested or asked to teach the material they learned. Following a study period, some students were asked to teach the material by providing a short video-recorded lecture, whereas other students did not teach. Then, all students completed a comprehension test that was either administered immediately or following a 1-week delay. Results indicated that students who only prepared to teach (without actually teaching) performed better than those who studied normally for a test on the immediate comprehension test; however, only students who prepared to teach and actually did teach the material showed benefits on the delayed comprehension test. A similar pattern of results was found in a recent study by Hoogerheide et al. (2014). Overall, this research suggests that the act of preparing and generating explanations encourages students to construct deeper meaning from the material, thereby promoting long-term understanding.

Related research by Roscoe (2014) and Roscoe and Chi (2008) indicates that—as with generating summaries and self-explanations—the quality of explanations generated for others is critical for achieving meaningful learning outcomes. In particular, some students may exhibit a *knowledge-telling bias*—that is, a tendency to merely restate the material with minimal elaboration (similar summaries that do not use the student's own words). The goal is for students to engage in *reflective knowledge building*, which involves generating inferences and actively reflecting upon one's own understanding of the material. Thus, reflective knowledge building is similar to our notion of engaging in generative processing—both involve actively constructing coherent mental representations by reorganizing and integrating the material with existing knowledge. Roscoe's research suggests that promoting meaningful interactions between students during learning by teaching—such as when the student-teacher is asked meaningful questions about the material—can help improve the quality of explanations generated (i.e., foster generative processing) and improve learning.

Practical Recommendations

Learning by teaching is a somewhat more complex learning strategy that can promote meaningful long-term learning under the right conditions. When implementing learning by teaching, it is important to consider the unique and interdependent roles of each stage of the teaching process—preparing to teach, explaining to others, and interacting with others. For example, as with self-explaining, the quality of the explanation that students generate is critical (i.e., the extent to which it involves reflective knowledge building as opposed to knowledge telling and the extent to which it contains accurate information). Studying with the expectation of later teaching the material (i.e., preparing to teach) may help students develop better quality explanations when they actually do teach. Answering questions from others during teaching may also help prime deeper cognitive processing, such as reflecting on one's own understanding and elaborating beyond the material to incorporate one's existing knowledge. The present state of the research supports asking students to practice explaining what they have learned to others, after they have initially processed a lesson with the expectation of later explaining it to others. Further research is needed to more closely examine ways to enhance the benefits of explaining to others, such as by helping students prepare to teach more effectively, or by fostering more productive interactions with peers.

Learning by Enacting

Learning by enacting involves engaging in task-relevant movements during learning, such as by manipulating objects or performing gestures in coordination with the lesson content. For example, children could be asked to place and move plastic models on a mat to represent the events described in a story. The benefits of enacting are often explained in terms of embodied theories of cognition and instruction (Barsalou 2008; Glenberg 2008; Paas and Sweller 2012; Pouw et al. 2014; Wilson 2002), which posit that cognitive processes are deeply grounded in one's physical interactions with the external world. Learning by enacting is also in line with generative learning theory, in that it helps learners use their prior knowledge to connect abstract concepts to concrete objects and actions, thereby enabling learners to construct a more meaningful mental representation of the material. In other words, learners must select relevant movements to perform, organize the to-be-learned material around the movements selected, and integrate this new representation of the material with their existing knowledge. Much of the research on enacting has tested the effects of asking younger students to perform gestures that represent problem-solving strategies in math (e.g., Cook et al. 2008), to manipulate objects—sometimes referred to as *concrete manipulatives* (Carbonneau et al. 2013)—to physically act out events described in a text (e.g., Glenberg et al. 2004), or to represent abstract math concepts (e.g., Fujimura 2001).

In an exemplary study investigating the effects of gesturing during learning, Cook et al. (2008) provided children with instruction in how to solve math equivalence problems. First, students were provided with preinstruction that was presented via speech (e.g., "I want to make one side equal to the other side"), gesture (e.g., by the instructor moving her hands under each side of the equation), or both gesture and speech. Children then either mimicked the instructor's speech, gestures, or both. On a subsequent delayed test of the material, students who were instructed to gesture significantly outperformed students who did not gesture. Overall, this study and other research by Goldin-Meadow and colleagues suggest that instructing students to engage in task-relevant gestures helps reduce cognitive demands by allowing students to use their body movements to help them represent problem-solving strategies (e.g., Goldin-Meadow et al. 2009; see Goldin-Meadow and Alibali 2013 and Novack and Goldin-Meadow 2015, for recent reviews); however, further work is need to examine the applicability of other types of gesturing techniques across different types of learning tasks.

Another form of learning by enacting involves manipulating objects, which has been shown to improve children's text comprehension. In a study by Glenberg et al. (2004), elementary school students read stories describing different scenarios (e.g., animals on a farm) and practiced manipulating toys to represent characters and events from the story (enacting group), or they only read the stories without access to the toys (control group). Results indicated that this form of enacting instruction improved children's ability to recall passages for which they manipulated toys, but this benefit did not transfer to new stories for which they did not manipulated toys. Thus, in follow-up experiments, children were provided with subsequent imagery instruction to help students internalize the process of manipulating objects so that they can apply the strategy to new situations. Indeed, this combined form of enacting and imagery instruction improved students' ability to apply the object manipulation strategy to new texts for which physical objects were not available. Many subsequent studies (e.g., Biazak et al. 2010; Glenberg et al. 2011; Marley and Szabo 2010; Marley et al. 2010) have found similar results with other student populations (e.g., preschoolers), learning materials (e.g., spoken passages), and types of manipulatives (e.g., virtual manipulatives). Overall, this research suggests that children are more likely to understand verbal material when they are able to make connections between the words and meaningful objects.

It is important to note that concrete manipulatives may only be useful under certain conditions. Unlike other generative learning strategies—which are most effective for less skilled learners or learners with lower prior knowledge—enacting may be most effective for higher skilled learners or for learners with higher prior knowledge (e.g., Fujimura 2001; Uttal et al. 1999). Enacting may create extraneous processing in students who do not possess the necessary prerequisite skills for seeing the connections between their movements and the academic content. Thus, students may need considerable practice with feedback to use manipulatives effectively.

Further, concrete manipulatives may be limited in their ability to help students apply their knowledge to new situations. In text comprehension, this may be mitigated by also providing students with imagery instruction in how to internalize the process of manipulating objects (Glenberg et al. 2004). In math instruction, one promising remedy is to use *concreteness fading* (Fyfe et al. 2014; McNeil and Fyfe 2012). Concreteness fading involves providing concrete materials (e.g., bundles of sticks) at the beginning of instruction to help learners ground the material in their prior knowledge, followed by gradually incorporating more abstract materials (e.g., math symbols) to help decontextualize the material and foster transfer.

Overall, learning by enacting is an emerging area of research in education, particularly for enhancing learning in science, technology, engineering, and mathematics (STEM; e.g., Marley and Carbonneau 2014). For example, recent studies have found learning benefits of asking students to trace graphs about temperature by hand (Agostinho et al. 2015) and to physically act out concepts such as torque and angular momentum (Kontra et al. 2015). This work on the inactive nature of science learning is promising (Hutto et al. 2015); more work is needed to more precisely account for how various forms of enactment that can promote appropriate cognitive processing during learning.

Practical Recommendations

Learning by enacting is a unique generative strategy because it involves using behavioral activity (by gesturing or manipulating objects) to support appropriate cognitive activity during learning. This more "embodied" view of learning is based on the idea that cognition and action should be viewed as interdependent rather than separate processes. To implement learning by enacting effectively, the research evidence suggests that students need explicit guidance in how to perform specific actions intended to promote learning—that is, guidance in how to map specific gestures to problem-solving strategies and math concepts, or how to map other body movements or specific object manipulations to underlying events described in a story, or to math or science concepts. In other words, similarly to other forms of instruction, students are unlikely to discover the appropriate gestures, movements, or manipulations on their own without explicit guidance and some prerequisite domain-specific skill. Overall, the main contribution of learning by enacting is to highlight the ability to use one's own body to promote generative processing and learning. More work is needed to expand the applicability of enacting methods to other tasks and domains, such as gesturing techniques across different concepts in math and body movements across different concepts in science.

Summary of Evidence for Generative Learning Strategies

As reported in Fiorella and Mayer (2015) and summarized in Table 1, each of the eight generative learning strategies is strongly supported by empirical research, yielding median effect sizes of d=0.4 or higher. According to Hattie (2011), instructional interventions with effect sizes of 0.4 or higher should be considered educationally relevant.

The first four strategies—summarizing, mapping, drawing, and imagining—involve translating to-be-learned material (often verbal material) into a different form of representation during learning: a summary, a map or matrix, a drawing, or a mental image. The act of translating across representations encourages learners to select the most relevant information for inclusion in the new representation, organize it into a coherent structure by building connections among the elements of information selected, and integrate it with existing knowledge by fitting the new structure with an existing structure. The final four strategies—self-testing, self-explaining, teaching, and enacting—involve somewhat further elaboration upon the material: generating answers to practice questions, explaining difficult portions of the material to oneself, teaching the material to others, and acting out the material with concrete objects. These strategies require more generating on the part of the learner, including more active use of one's prior knowledge to restructure the material into a more meaningful representation.

The eight strategies can also be classified based on the mode of representation constructed by students during learning. Summarizing, self-testing, self-explaining, and teaching involve generating a primarily verbal representation of the material (verbal generative strategies), whereas mapping, drawing, imagining, and enacting involve generating a spatial representation of the material (spatial generative strategies). According to generative learning theory, selecting the most appropriate strategy for a given learning situation depends on both the prior knowledge of the learner and the nature of the to-be-learned material Wittrock (1989). Verbal generative strategies may be most appropriate when the material is not highly complex or

Table 1 Evidence for eight generative learning strategies (from Fiorella and Mayer 2015)

Strategy	Description	Comparisons	Median d
Summarizing	Create a written or oral summary of the material	26 of 30	0.50
Mapping	Create a concept map	23 of 25	0.62
	Create a knowledge map	5 of 6	0.43
	Create a matrix organizer	8 of 8	1.07
Drawing	Create a drawing that depicts the text	26 of 28	0.40
Imagining	Imagine a drawing that depicts the text	16 of 22	0.65
Self-testing	Give yourself a practice test on the material	70 of 76	0.57
Self-explaining	Create a written or oral explanation of the material	44 of 54	0.61
Teaching	Explain the material to others	17 of 19	0.77
Enacting	Move objects to act out the material	36 of 49	0.51

spatial in nature, when the learner is able to internalize (i.e., mentally imagine) relevant spatial relations on their own without the need to create an external representation, or when an external spatial representation (e.g., a diagram or picture) is already provided (and thus, assisting in the formation of an internal spatial representation). On the other hand, spatial generative strategies may be most appropriate when the materials is highly complex or spatial in nature, when the learner is unable to internalize the relevant spatial relations on their own, or when an appropriate external spatial representation is not provided. Thus, spatial generative strategies may be especially useful when learning complex spatial concepts related to STEM (e.g., Stieff et al. 2014).

Many of the strategies—such as summarizing, mapping, drawing, and self-explaining—tend to be most effective for students who are less skilled or have low prior knowledge. This is likely because students who are higher skilled or who have high prior knowledge already use effective learning strategies spontaneously or they have acquired enough background knowledge that they do not benefit from creating an external representation of the material. It is important to note that while less skilled students may benefit from using generative learning strategies, they may need guidance or explicit training in how to use the strategies effectively. Ultimately, the effectiveness of generative learning strategies depends on the quality of what is generated by the learner—that is, the extent to which students are able to construct a coherent mental representation of the material during learning.

Some of the strategies—such as imagining or enacting—tend to be more effective for students who are higher skilled or have high prior knowledge. This is likely because using these strategies can be cognitively demanding—such as having to generate and maintain a complex mental image in working memory or recognizing the link between one's physical movements and underlying abstract concepts. Again, this suggests that using generative learning strategies requires baseline level of requisite knowledge and skill. Research suggests that this can generally be achieved through relatively brief training, such as instructor modeling followed by practice with feedback. Overall, students need to know which strategies to use, when to use them, and how to use them effectively.

The Future of Generative Learning

According to generative learning theory, learning is a sense-making activity, which involves building cognitive structures that can be used in new situations. Thus, research on generative learning strategies would benefit from a greater focus on assessing meaningful learning outcomes such as comprehension and transfer, rather than rote learning outcomes such as recall. Similarly, research should place a greater emphasis on assessing the durability of learning strategies over time by administering learning outcome measures following a delay, rather than primarily focusing on immediate learning. Interestingly, the extent to which existing research follows these two recommendations varies considerably depending on the strategy investigated. For example, research on learning by self-explaining often uses meaningful learning outcome measures administered immediately, whereas research on self-testing often uses rote learning outcome measures administered after a delay. In short, future research should consider the effects of generative learning strategies on different types of learning outcomes (including measures of meaningful learning) and at different retention intervals (including delayed tests). In general, using generative learning strategies should result in meaningful and persistent learning outcomes or what Wittrock (1974) referred to as "long-term memory plus transfer to conceptually related problems" (p. 89).

Another consideration for the future of learning is to incorporate valid process measures that provide more precise insight into the specific cognitive and metacognitive mechanisms underlying generative learning strategies. Frequently, performance on a learning outcome test is used to make inferences about specific processes taking place during learning. Although in some cases such inferences may be valid, it of course introduces the possibility of circular reasoning, in which cognitive processes and learning outcomes are used to explain themselves. Thus, it is important for researchers to develop measures of processes and strategies used during learning to verify whether using a particular learning strategy has indeed caused the predicted effect. Importantly, such measures should be grounded in a theory of how people learn that allows for specific predictions. For example, process measures can be used to analyze the quality of what students generate during learning—such as the quality of students' summaries (e.g., Hooper et al. 1994), explanations (e.g., Chi et al. 1989; Roscoe 2014), maps (e.g., Holley and Dansereau 1984), or drawings (e.g., Schwamborn et al. 2010)—and to analyze the time students spend learning and engaging in generative strategies (e.g., Selig et al. 2012). Eye tracking may also provide insight into the cognitive processes underlying generative learning, such as how students make internal connections between elements of information in a lesson (e.g., Ponce and Mayer 2014).

Future research should also integrate the roles of motivational and metacognitive processes in generative learning (Mayer 2014). According to generative learning theory, meaningful learning requires that the learner is motivated to invest effort toward making sense of the material—that is, to engage in the cognitive processes of organizing and integrating. It is important to develop a better understanding of how students' goals, beliefs, interests, and attributions influence generative processing and how instructional methods can be used to motivate learners to use more effective learning strategies. For example, students may hold unproductive beliefs about their own learning—such as attributing learning to general ability rather than effort—that may cause them to be demotivated and use suboptimal strategies (e.g., Blackwell et al. 2007). Instructional methods aimed at fostering productive beliefs may, in turn, foster more productive learning strategies (e.g., Muis et al. 2015b; Paunesku et al. 2015).

Students not only need to know how to use a strategy and be motivated to use it, but they must also know when to use which strategy—that is, students must able to regulate their own learning. Research on metacognition and learning suggests that students are generally poor judges of their own learning (Dunlosky and Lipko 2007; Lin and Zabrucky 1998). Inaccurate judgments of learning can then result in students using suboptimal strategies and ultimately achieving poor learning outcomes. There is some evidence that asking students to use generative strategies such as summarizing Thiede and Anderson (2003), creating a concept map (Redford et al. 2012), or generating key words (Thiede et al. 2003) can improve metacognitive calibration. Further, using generative strategies such as self-testing can help students engage in more effective restudying behavior (Little and McDaniel 2015). Thus, in addition to providing cognitive benefits, generative learning strategies also appear to offer metacognitive benefits by providing students with more accurate information regarding their current understanding of the material.

Similarly, research should explore how students select between and employ multiple types of generative strategies during learning. According to generative learning theory, whether a student should create a verbal summary, an outline, a map, or a drawing will likely depend on the material's underlying structure, which can change throughout a lesson. For example, scientific texts can follow different basic structures such as generalization, sequence, or compare and contrast (Cook and Mayer 1988). It would be useful to examine the extent to which learners spontaneously adapt their strategy choice based on the structure of the to-be-learned material.

The issue of switching across strategies during a given lesson also relates more broadly to how students can incorporate multiple strategies across various learning or study situations—or what can be referred to as *strategy clusters*. For example, consider the strategies that may be clustered across four common learning situations: (1) taking notes during a lecture, (2) reviewing notes following the lecture, (3) reading a textbook, and (4) studying for an exam. Given the time constraints of learning from lectures, the best a student may hope for is to take concise summary notes of the lecture material with minimal use of spatial strategies (such as by writing summary bullet points and a basic outline). Reviewing one's notes after lecture can serve as a time for students to rearrange one's notes spatially by building connections and elaborating on the material (such as by creating a knowledge map, a graphic organizer, or a drawing) and to test oneself by self-explaining and answering practice questions. While reading the textbook, a student may engage in a similar process of creating summary notes, spatializing one's notes, self-explaining the material, and answering practice questions (such as those provided by the textbook). Finally, when studying for an exam, the focus may be more heavily on retrieval activities, such as generating and answering more practice questions and self-explaining the material. This may also be an appropriate time for students to explain the material to others (i.e., learning by teaching) because by that point, they may be able to effectively generate a quality explanation of the material and be ready to benefit from receiving questions from others.

Overall, it is perhaps more accurate to think of each of the generative strategies as appropriate within particular learning and studying contexts, rather than to think of one strategy as being the *most* effective. Of course, the strategy clusters described above (although informed by existing research on effective learning strategies) are hypothetical, and further research is needed to explore interactions among strategies across different contexts.

Finally, research is needed to better understand how individual differences among students influence strategy use. According to generative learning theory, the most important individual difference among students is domain-specific prior knowledge (Mayer 2014; Wittrock 1989). However, other differences such as in general ability (e.g., math, verbal, and spatial ability), metacognitive skill, or motivation may moderate effects of using generative learning strategies. For instance, strategy training may help compensate for lower general cognitive ability.

In conclusion, two routes to improving student learning are through improvements in the instruction (i.e., instructional methods) or through improvements in the learner (i.e., learning strategies). Although much research attention has been given to the effectiveness of instructional methods and the development of instructional design principles, this review demonstrates the benefits of also considering the role of learning strategies in improving learning outcomes and points to the resurgence of useful research on learning strategies. On the practical side, this review has shown the promise of eight learning strategies, which have been shown to improve performance on learning outcome tests with effect sizes in the medium-to-large range. An important next step is to better document the conditions under which each strategy is most effective. On the theoretical side, this review provides evidence in support of generative learning theory, which posits that meaningful learning depends on the learner engaging in appropriate cognitive processing during learning. An important next step is to better examine cognitive processing during learning in addition to test performance and to incorporate the roles of motivation and metacognition.

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