INSTRUCTION BASED ON SELF-EXPLANATION

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INTRODUCTION

Over twenty years of research has documented the fact that explaining a concept aloud to oneself enhances learning and aids in comprehension monitoring. How powerful is this technique and to what extent is it superior to many other, more commonly employed learning strategies? The goal of this chapter is to review the literature on the self-explanation effect in the context of a theoretical framework based on the overt activities of the learner. We begin with a discussion of the self-explanation effect, followed by a brief description of the *passive-active-constructive-interactive* theoretical framework. Then we compare self-explaining with other learning strategies in the context of this framework.

HISTORICAL OVERVIEW

Research across a variety of domains has consistently supported the finding that students learn better when they explain to themselves the material they are studying. Known as the *self-explanation effect* (Chi, Bassok, Lewis, Reimann, & Glaser, 1989), the phenomenon has been studied across age groups, domains, and instructional formats (Bielaczyc, Pirolli, & Brown, 1995; Chi, de Leeuw, Chiu, & LaVancher, 1994; Ferguson-Hessler & de Jong, 1990; Hausmann & Chi, 2002; McNamara, O'Reilly, Best, & Ozuru, 2006; Renkl, Stark, Gruber, & Mandl, 1998; Siegler, 1995; Wong, Lawson, & Keeves, 2002) and research studies have repeatedly found that attempting to clarify an idea by explaining to oneself leads to enhanced learning, more accurate self-assessments, and more effective problem-solving. The purpose of this review is to demonstrate that the process of self-explaining is a *constructive* learning activity and the effectiveness of self-explaining compared to other learning activities can be understood within a framework of *passive-active-constructive-interactive* learning strategies.

The goal of the learner is to convert information into usable skills and knowledge. Within a classroom context, that information often comes in the form of words and examples generated from a teacher or text. Successful learning strategies should assist the student in his or her attempt to construct this new knowledge. Self-explaining is a learning strategy in which a learner elaborates upon the presented sentences or example lines by relating them to prior knowledge, making inferences from them, and integrating them with prior text sentences or example lines. For example, if two text sentences about the human circulatory system say that:

> *The septum divides the heart lengthwise into two sides.*
>
> *The right side pumps blood to the lungs, and the left side pumps blood to the other parts of the body*

then a student can self-explain by saying aloud "So the septum is a divider so that *the blood doesn't get mixed up*. So the right side is to the lungs and the left side is to the body. So the *septum is like a wall . . . separates it*" (Chi, 2000). In this self-explanation, the student is inferring that the septum is a solid divider and its function is to prevent the blood from mixing. Note that self-explanations are the generated inferences (italicized) that go beyond the text sentences. Moreover, self-explanations do not have to be generated overtly; the processes of generating inferences and integrating new information with prior

knowledge can be done covertly. Experimentally, in order to collect data, we requested that students self-explain aloud.
Chi et al. (1989) observed students studying worked-out solution examples of physics problems and found that the most successful performers generated more self-explanations than the less successful performers. In addition, they found that the self-explanations from the successful students were more principle-based than those generated by the poorer performing students. Numerous studies in the domain of procedural learning have replicated the relation between the generation of self-explanations and enhanced learning outcomes. For example, increases in self-explanations have been associated with learning gains in the areas of computer programming (Pirolli & Recker, 1994), applications of principles of electricity and magnetism to Aston mass spectrometry (Ferguson-Hessler & de Jong, 1990), and solving algebra word problems (Nathan, Mertz, & Ryan, 1994). The positive impact of self-explanation on problem-solving ability has been replicated under a variety of conditions (Bielaczyc, Pirolli, & Brown, 1995; Chi et al., 1994; Neuman & Schwarz, 1998; Renkl, 1997, 2002; Renkl, Stark, Gruber, & Mandl, 1998).

To investigate if this learning strategy could be experimentally manipulated and to explore the impact of self-explanations in a conceptual domain, Chi et al. (1994) compared learning of the circulatory system between a group of eighth grade students prompted to self-explain with a control group instructed to read the same text twice. The researchers found that the self-explanation group showed greater gains in learning from the pre-test to the post-test and furthermore, the students that generated the largest number of explanations showed the greatest gains in learning.

Subsequent research proceeded to test specific instructional regimens for the subjects to be trained in self-explanation procedures (Bielaczyc et al., 1995). A number of successful training programs have been designed to teach students self-explanation on a large scale. For example, McNamara (2004b) developed a self-explanation reading training program (SERT) and found that training significantly improved text-based comprehension during training compared to reading aloud alone for a group of psychology undergraduate students studying science-based text passages. When the researchers examined post-training comprehension, they found that the high knowledge readers did not show a benefit of the SERT training but low knowledge readers in the SERT condition doubled their comprehension scores when compared to the control read-aloud condition. Following the success of the human one-to-one training program of SERT, a web-based application called the Interactive Strategy Training for Active Reading and Thinking (iSTART) was developed and has also been shown to improve both high and low prior knowledge students' reading comprehension scores when compared to students who did not receive iSTART training (McNamara, Levinstein, & Boonthum, 2004; McNamara, O'Reilly, Best, & Ozuru, 2006). The research studies overwhelmingly demonstrated that self-explanation could be taught and that subjects in the self-explanation groups generated a higher number of self-explanations and performed better on a variety of learning outcomes across multiple domains.

Other research has focused on the optimal conditions under which self-explanation is found to have a beneficial learning impact. For example, does self-explanation work better for students with high or low prior knowledge? Are there specific prompts that elicit more or less self-explanations? And does the self-explanation technique work for all age groups? The following studies described below were designed to address these questions.

With regard to high and low prior knowledge, the self-explanation effect has been demonstrate in both group and even in subjects where the learner has little to no prior knowledge of the topic (de Bruin, Rikers, & Schmidt, 2007). Further, Ferguson-Hessler and de Jong (1990) found that although good and poor performers did not differ in the number of study processes they engaged in during a problem solving task, they did differ in the type of study process used, with good performers using a greater number of integrative study processes and poor performers more likely to engage in superficial processing. For example, in a study of the effects of self-explanation training and worked-out examples in bank tellers' learning about compound and real interest (Renkl et al., 1998), it was found that training on self-explanation primarily benefited low prior topic knowledge subjects, especially on a near-transfer task. In this study, the self-explanation training consisted of modeling self-explanation behavior for one example and coaching the learner in a second example. All learners were instructed to "think aloud" throughout the entire experiment. The benefit for the low prior knowledge learners may have arisen from the fact that self-explanation allowed them to fill in gaps in their knowledge.

Further investigations into the optimal conditions on self-explanation found that prompted self-explanation improved problem-solving scores in a far-transfer test (e.g., see Wong, Lawson, & Keeves, 2002). The findings of Wong et al. suggest that prior knowledge also interacts positively with the self-explanation effect in that the greater the existing knowledge base, the more advantage of the self-explanations. Although there is some inconsistency in the findings of several studies with respect to whether self-explaining benefits the low or high prior knowledge learners more, one interpretation of such mixed results is that it can benefit both low and high prior knowledge learners for different reasons. For individuals with high prior knowledge, the act of self-explaining may allow them to repair their existing mental models and thus improve learning outcomes, whereas for individuals with low prior knowledge, the act of self-explaining may allow them to generate inferences to fill gaps of missing knowledge (Chi, 2000).

Other studies examined whether the format of the study material had an impact on learning from self-explanation. For example, Ainsworth and Loizou (2003) found that students presented with diagrams generated significantly more self-explanations and showed greater learning outcomes than students presented with the material in a text-only format. Further, Butcher (2006) found that simple diagrams led to more inference generation in college students studying the circulatory system when compared with students presented with text only or complex diagrams.

With regard to age, the self-explanation effect has been found in subjects as young as 5-year-olds. Siegler (1995) found that 5-year-old children asked to explain an expert's reasoning performed significantly better than those asked to explain their own reasoning or those not asked to explain at all. Siegler proposed that much of children's learning in general comes from trying to explain other people's reasoning.

However, there have also been reported instances in which self-explanation did not lead to greater learning (e.g., Hausmann & Chi, 2002; Mwangi & Sweller, 1998). There are generally two explanations for such failed results. One explanation is that a large number of self-explanations were not generated. For example, when students were asked to type their explanations, the number of self-explanations generated reduced significantly along with the positive learning gains from this learning strategy (Hausmann & Chi, 2002). However, this smaller quantity can be increased by increasing the number of prompts, even for typed explanations (Aleven & Koedinger, 2002). Another explanation is that sometimes what is generated are not self-explanation inferences, but merely paraphrases (Teasley, 1995). In these cases, essentially no self-explanations were produced, therefore it is not surprising that no increased learning took place.

What is it about self-explanation that has made it such a successful learning strategy? Several cognitive mechanisms underlying the self-explanation effect have been proposed. The two mechanisms with the greatest amount of empirical support are that self-explanations allow learners to identify and fill in knowledge gaps, and that self-explanations aid learners in the construction and repairing of their mental models (Chi, 2000). In support of the dual underlying cognitive mechanisms mediating the self-explanation effect, Ainsworth and Burcham (2007) manipulated the coherence of an expository text about the circulatory system and measured learning in groups of university students who received self-explanation training and those who did not. The researchers found that the greatest learning occurred with the maximally coherent text, suggesting that self-explanations are not only used to fill in missing information or knowledge gaps, but also may support knowledge revision and mental model repair. For minimally coherent texts, self-explanation seems to be used primarily to generate inferences and fill in the missing information.

THEORETICAL FRAMEWORK: PASSIVE-ACTIVE-CONSTRUCTIVE-INTERACTIVE

To improve learning, it has been widely proposed in the literature that students engage in active learning, as opposed to passive learning. *Active learning* is broadly defined as encouraging learners to pay "attention to relevant information, organizing it into coherent mental representations, and integrating representations with other knowledge" (Mayer, 2008, p. 17). However, many learning activities have been proposed that encourage students to pay attention, organize, and integrate new information with knowledge, and it is not clear which activities are superior for learning. Chi (2009) provided a framework for active learning by differentiating students' learning activities into four types: *passive*, *active*, *constructive*, and *interactive*. The framework classifies the four types according to the observable overt activities that occur during learning along with the hypothesized underlying learning processes. In addition, the framework suggests a testable hypothesis with regard to the type of learning activities that should lead to the greatest learning outcomes.

In the following section, we first more clearly delineate the framework for classifying *passive*, *active*, *constructive*, and *interactive* learning activities, and then we briefly discuss the testable hypothesis specifically in relation to the self-explanation effect. The remainder of the chapter consists of direct comparisons between self-explanation learning conditions and groups engaged in either passive, active, constructive, or interactive activities. For the framework outlined below and first proposed by Chi (2009), a learning activity is classified by observable, overt actions on the part of the learner. The actions can be manipulated by the researcher or instructor and can be assessed, coded, and analyzed in a variety of ways as evidence of learning.

Passive Learning Activities

A *passive* learning activity is defined as any learning situation in which the learner is essentially not engaging in any overt activity related to the learning task. Some examples of passive activities include listening to a lecture, watching a video, or reading a text without engaging in any additional activity such as note-taking, highlighting, or underlining. Of course, it is always possible that the learner's attention may be engaged in the learning task but without overt confirmation of such engagement, the conservative approach is to classify this level of behavior as a passive learning situation since the learner may be zoning out a large proportion of the time. It is also entirely possible of course that an overtly passive learner is processing deeply, but merely does not exhibit any observable behavior. For example, it is possible that an individual is engaged in a passive behavioral activity, such as reading silently without taking notes or underlining the text passages, and yet is employing deep underlying comprehension processes. However, for the purpose of comparing different overt activities that can be manipulated, say, by a teacher in a classroom, we can only rely on a single metric for classification purposes, and the metric is the amount of learning activities that are directly observable. For example, Williams and Lombrozo (in press) tested subjects' abilities to recognize underlying patterns of category membership under two different conditions. The first group was instructed to self-explain aloud and the second group was not prompted to engage in any specific learning strategy. According to our classification scheme, the second "unprompted" group would be labeled as passive, since they did not engage in any overt activity related to the learning task. Clearly, the possibility exists that the individual learners were engaged in a variety of covert study strategies, however, we would still classify this as passive since the subjects were not being forced to engage in an overt learning activity. Our theoretical framework assumes that if subjects are forced to do something overtly, then they are more likely to learn. This is in fact what Williams and Lombrozo found, with the self-explain group performing significantly better than the unprompted study group on a number of learning outcome measures. In fact, the self-explain group showed superior learning even though approximately one-third of the subjects in the unprompted group reported covertly trying to explain during the study session of the experiment, supporting our hypothesis that subjects are more likely to learn if they are required to engage in an overt learning strategy. Moreover, our assumptions pertain to relative differences. That is, we are assuming that a learner who overtly undertakes some learning behavior is more likely to be cognitively engaged than a learner who does not behaviorally exhibit any learning activities. Therefore, we assume the overt behavioral activity corresponds to the minimum underlying cognitive processes required to produce the behavior. The cognitive processes proposed for the passive level of the taxonomy can be thought of as at best direct storing of the presented information, in sort of an episodic memory way as to be able to repeat it back verbatim. Or at worst, the learner is not engaged in any learning processes and is zoning out.

Active Learning Activities

In order to categorize a learning activity as an *active* activity, the learner must be engaged in doing something physical while learning. A simple contrast would be between the passive activity of reading a text versus the active activity of highlighting while reading a text. The difference is that in the latter, the learner is performing a physical task that provides an overt measurement of paying attention. Numerous examples exist in the literature of active learning activities including pointing or gesturing, underlining a text, copying and pasting, repeating sentences verbatim, copying problem solution steps, delete-and-substitute summarizing, clicking on the screen in a computer environment, navigating a website, selecting an answer from a list of choices, and matching two columns of concepts and their definitions.

As can be seen from the list, the criterion for active activities is that the learner is visibly engaged with the learning materials thereby increasing the likelihood for learning to occur. The underlying cognitive processes that may be mediating this learning can be thought of as assimilating processes and could include attending to the presented materials, thereby activating and strengthening relevant knowledge, searching for related knowledge, and encoding new information in the context of the relevant activated knowledge or instantiating new information in the context of an existing schema (Chi, 2009). These processes have the potential to enhance learning by strengthening existing knowledge and adding the newly presented knowledge among other possibilities. The difference between direct storing in the case of passive activity and assimilating in the case of active activity is that in assimilating, the learner is not only paying attention to the materials that are being actively manipulated (such as the underlined sentences), but the activity (of underlining, for example) often involves selecting parts of the materials so that it enhances the potential of activating prior knowledge pertaining to the material that is being attended to, therefore the new information is more likely to be assimilated into a relevant context. If passive learners are storing any new information at all, it is done mindlessly in an episodic way without a consideration of its proper context.

Constructive Learning Activities

When a learner goes one step further than simply engaging in a physical activity and produces some additional output that contains information beyond that provided in the original material, then we can classify this behavior as a *constructive* learning activity. Specific examples of constructive learning activities include generating self-explanations, constructing a concept map, asking questions, drawing a diagram, comparing and contrasting cases or examples, and constructing a timeline. As is illustrated by the examples, constructive activities require the learner to produce some overt output (e.g., an explanation, a map, a question, a diagram, a timeline, etc.) and the output must go beyond the given information. As the case for classifying a learner as passive or active, a learner of course can be constructive without exhibiting any overt behavior. However, for the purpose of classification, we can rely on a single metric in order to infer learning using the same observable dimension of behavior.

It is also important to note that in order to verify that a learner's overt activity is truly constructive, the researcher or instructor needs to examine the generated output to confirm that it does indeed go beyond the provided information. For example, if a student is asked to "think aloud" during a learning task, the verbal protocols would need to be analyzed to determine if the articulations fall into the active or constructive categories. Articulations that would place the learning activity in the active category would include items such as verbatim repetitions, nonsense phrases, or paraphrases, while statements defined as elaborations or inferences would place the learning activity in the constructive category since such statements demonstrate that the learner produced output beyond the original material, such as descriptions of new spatial relations.

The creating processes required for constructive learning activities may mediate learning through the underlying cognitive mechanisms of inference generation and mental model repair as proposed for the self-explanation effect (Chi, 2000). These mechanisms may work by enriching existing knowledge, along with repairing existing knowledge to make it more coherent, accurate or better structured.

Interactive Learning Activities

The final category in the learning activity taxonomy is that of *interactive* learning activity. This final category is inherently more complex than the three preceding classifications in many ways. For one thing, a learner can interact either with a peer, an expert, or a system such as a computer-tutoring program. As a starting point to classify interactive learning activities, Chi (2009) focused solely on dialoguing among dyads as a form of overt interactive activities. In order to be classified as interactive, the dialogue must include substantive contributions from both partners with neither partner's contributions being ignored. The dialogue can be between an expert and a novice and would be characterized by activities such as responding to scaffoldings, revising errors based on feedback, and responding to the expert's questions. In addition, the dialogue can be between two peers and would contain dialogue patterns that build on each other's contributions, confronts or challenges the partner's statements, argues and defends the learner's own case, and ask or answer each other's questions. Again, it is critical that the verbal protocols of the partners be analyzed to ensure that an interactive learning strategy is actually in place. If the analysis finds that only one partner is making substantive contributions or the partners are ignoring each other's contributions and simply taking turns speaking, then those activities would not be categorized as an interactive learning event.

In sum, an interactive learning situation includes the cognitive mechanisms of creating and assimilating that have been proposed to mediate learning in the constructive and active learning activities respectively. From the perspective of the individual learner, the creating and assimilating processes appear to be similar in interactive and constructive activities, the question arises as to why being interactive would lead to enhanced learning more so than merely being constructive. One explanation may be that in an interactive environment, the learner has the additional advantage of a partner's contributions that can be a valuable source of additional information, a new perspective, or corrective feedback to name a few possibilities. In addition, a dyad has the potential of creating a shared understanding together that may be more novel or deeper than either could create in isolation. Thus, for our current discussion here, we expand interaction to include dialoguing with any kind of a system (such as an Intelligent Tutoring System), and thus the commonality of interaction more broadly includes additional information that is provided in the form of feedback, elaboration, critiques, questions, and challenges, among other possibilities. Table 15.1 provides a summary of the passive-active-constructive-interactive theoretical framework along with examples of overt learning activities and possible underlying cognitive mechanisms.

Table 15.1 Characteristics of the passive-active-constructive-interactive theoretical framework

	Passive	Active	Constructive	Interactive
Observable overt learning activity	No physical activity	Doing something physically	Producing novel outputs	Dialoguing with substantive contributions
Examples of overt learning activities	Listening to a lecture, watching a video, reading a text	Highlighting a text, pointing or gesturing, underlining a text, copying and pasting, clicking on a computer screen	Generating self-explanations, creating a concept map, asking questions, drawing a diagram, comparing and contrasting cases	Responding to scaffolding, responding to expert's questions, challenging a partner's statements, asking and answering each other's questions
Possible underlying cognitive processes	Direct-storing processes	Assimilating processes	Creating processes	Jointly creating and assimilating processes
Expected cognitive learning outcomes	Storing information in an "episodic" manner without regard to context	Activating and strengthening prior knowledge, storing information in a meaningful way	Generating inferences, repairing mental models	Encoding corrective feedback, taking new perspectives, creating novel understanding
Expected overt learning outcomes	Minimal	Greater than passive	Greater than passive or active	Greater than passive, active, or constructive

CURRENT TRENDS AND ISSUES: A TESTABLE HYPOTHESIS WITH

REGARDS TO SELF-EXPLANATION

The framework described above along with the possible underlying cognitive processes suggest the testable hypothesis that active learning activities produce greater learning outcomes (especially on measures of deep learning) than passive, constructive is better than active, and interactive is better than constructive. Evidence in the literature testing this hypothesis has been presented by Chi (2009). The purpose of the present chapter is to examine this hypothesis within the specific context of the self-explanation effect. According to the proposed taxonomy, self-explaining would fall under the category of constructive activity since by definition, self-explanations include inferences beyond the presented materials (Chi, 2000).

Accordingly, research studies comparing self-explanation to passive or active learning activities, should find that the self-explanation groups exhibit the greatest learning, particularly on measures of deep learning. Additionally, studies in which self-explanation is contrasted with another constructive activity should find minimal differences in learning outcomes. Any differences that do exist between the constructive activities would need to be explained, perhaps in terms of the task demands. Finally, the interactive activities between peers or between peers and experts should yield greater gains than subjects engaged in self-explaining alone. Again, it is important to note that the taxonomical classification of the learning activities of the research studies to be examined are based on the overt learning activities as described in the study and thus may differ from the authors' original categorizations and descriptions.

The following section examines the available literature on the self-explanation effect in comparison with passive, active, other constructive, and interactive learning activities. The illustrative studies we cite are based on the learners' overt activities (not necessarily the authors' intent), are limited to those that manipulated only one activity in a given condition, and when possible, focus on measures of deep learning. In addition, we provide systemic labels for the conditions in a way that makes them more easily compared, and calculate effect sizes for significant finding. The effect sizes, when not stated in the research study, were calculated as *Cohen's d* by dividing sample mean differences by pooled variances using either stated means and standard deviations, *t*-test values or F-test values according to the formulas defined in Thalheimer and Cook (2002) and based on the procedures originally detailed by Rosnow and Rosenthal (1996) and Cohen (1992).

Self-Explanation versus Passive Learning Activities

As a *constructive* activity, self-explaining should show clear learning outcome advantages when compared to *passive* learning strategies such as reading a text, listening to a lecture, or watching a video (again, assuming that passive learners are less likely to be engaged fully in appropriate cognitive processing relative to constructive learners). Studies comparing self-explanation to passive activities are prevalent in the literature and we have selected five studies to illustrate this contrast below.

In one of the original studies investigating the effectiveness of self-explanation as a learning strategy, Chi et al. (1994) tested eighth-grade students' declarative knowledge of the circulatory system under two different learning conditions. In the self-explain text condition, the students were prompted to generate explanations after reading each sentence of the text, thus this condition consists of a constructive activity requiring the subjects to generate output that goes beyond the provided information. In contrast, under the read-twice condition, the students were instructed to read the same text passage twice, so the read-twice group would fall into a passive learning activity as they were not engaged in doing something physical and also did not generate any additional overt output. An examination of post-test scores found that the self-explain text group significantly outperformed the read-twice condition. In particular, for the two categories of questions that were designed to assess deeper levels of understanding by requiring use of prior knowledge and knowledge inferences, the self-explain text group showed a 22.6% gain while the scores for the subjects in the read-twice condition only improved by 12.5%, $t\ (22) = 2.64$, $p < 0.01$, with a large effect size of $d = 1.14$.

Similarly, in a study of novice chess players, de Bruin et al. (2007) compared learning outcomes for a group of college students instructed to predict the next move of a computer opponent and self-explain why that was the correct move (self-explain + predict group) with a group instructed only to predict the next move by physically placing the chess piece in the predicted location (predict group) and with a third group instructed to simply observe the moves made by the computer (observe group). The comparison of interest for this section is between the self-explain + predict group with the observe group. The self-explain + predict group was not only required to do something physical (i.e., make a prediction in terms of placing a chess piece), they were also required to produce some additional output that was not contained in the original material (i.e., to generate explanations as to why the predicted move was the correct move to make).

According to the taxonomy detailed in the previous section, the self-explain + predict group clearly falls into the constructive learning activity category. On the other hand, the observe group was instructed to simply watch the computer as the simulated chess game progressed. The subjects were not asked to perform any manipulations or generate any outputs and thus this group falls into the passive category of learning activities. The researchers then looked at the number of checkmates achieved for each group in the test phase. As the framework predicted, the self-explain + predict condition attained significantly more checkmates ($M = 3.00$, $SD = 1.77$) than the observe group ($M = 1.33$, $SD = 1.68$). This difference was significant with a large effect size of $d = 0.97$. In fact, the subjects in the constructive condition achieved twice as many checkmates as the subjects in the passive condition, providing further support for our hypothesis that the success of the self-explanation effect may be attributed to the constructive nature of the learning activity.

In another study that looked at the effectiveness of reading as a learning activity, Griffin, Wiley, and Thiede (2008) divided college undergraduates into three groups: one group was instructed to read the text only once as if they were to be tested on the material (read-once group), the second group was instructed to read the text once quickly and then a second time more thoroughly as if they were to be tested on the material (read-twice group) and the third group was instructed to read the text once and then a second time during which they should try to explain the material to themselves (self-explain text group). This study provides a clear contrast between the constructive activity of self-explaining and the potentially more passive activity of reading and re-reading. Again, the researchers found that the constructive learning activity of self-explanation significantly improved accuracy over the passive learning activities of reading once and of reading twice ($M = 0.63$, $SD = 0.38$ for the self-explain text group versus $M = 0.21$, $SD = 0.49$, $d = 0.95$ for the read-once group and $M = 0.39$, $SD = 0.38$, $d = 0.63$ for the read-twice group).

In a study investigating children's learning abilities, Pine and Messer (2000) investigated 5–9-year-old children's performance on a balance beam task before and after a demonstration by the instructor. In the self-explanation condition, the children were asked to explain how the instructor was able to balance the beam (self-explain expert condition) while in the observe condition the children were instructed to just watch and were not invited to make comments. This study represents an example of a constructive learning strategy (self-explanation) compared directly to a passive learning strategy (sit and watch the instructor). This study is particularly interesting, since this specific passive strategy is commonly employed in the classroom—even with the seemingly more involved activities such as classroom demonstrations. Pine and Messer found that significantly more children improved in the self-explain expert condition (70%) when compared with the observe condition (50%) and in addition, the amount of improvement as measured by gain in mental model shift was significantly greater for the self-explanation condition than for the observe condition $F(1,74) = 8.96$, $p = 0.003$, $d = 0.61$.

Although the passive learning strategy of simply listening to a teacher explain a concept may be one of the most commonly employed strategies in the classroom, only a limited number of studies have compared the effectiveness of this technique to self-explanations. In one study, Pillow, Mash, Aloian, and Hill (2002) investigated the effects of self-explanation on 4- and 5-year-olds' ability to predict misinterpretations of ambiguous pictures. The training conditions in this study consisted of having the children explain their own misinterpretations (self-explain own), explain the misinterpretations of a puppet viewing similar drawings (self-explain puppet), or simply view the drawings while the experimenter discussed the drawings (observe).

The first training condition, self-explain own, clearly fits the definition of self-explanation and thus provides a direct comparison between the constructive learning activity of self-explaining and the passive activity of watching the drawings and listening found in the third condition of observe. In addition, the second training condition (self-explain puppet) also fits into the definition of self-explanation and is similar to the task of self-explaining a text or instructor. The researchers' findings were as anticipated with a significant effect between both explaining groups (self-explain own and self-explain puppet) versus the passive no explaining group (observe). Specifically, the researchers measured the percentage of trials in which the children correctly identified the misinterpretation between what they or the puppet "thought" the drawing was and what the picture really was in "reality." This measure was labeled the "think-reality contrast" score and the group found that 4-year-olds in the self-explain own condition displayed a post-test think-reality contrast score of 65% ($SD = 33.60$) and the self-explain puppet condition had a score of 79% (SD = 45.03) while the same age group in the observe condition had a "think-reality contrast" score of only 48% ($SD = 38.43$). This difference was significant with moderate to large effect sizes of d =0.46 and $d = 0.73$, respectively.

In summary, all five studies described above illustrate the advantage of the constructive strategy of self-explanation over passive learning activities commonly used in the classroom. Table 15.2 summarizes the five studies of this section and shows that self-explanation is superior to a variety of passive activities, with an overall mean effect size of $d = 0.78$, which is close to being a large effect.

Table 15.2 Summary of studies: self-explaining (SE) versus passive

Study	Age group	Text/task	Results	Effect size
Chi et al. (1994)	Children (eighth grade students)	Read circulatory system text	SE text > Read-twice	*d* = 1.14
De Bruin et al. (2007)	College students	Predict computer chess moves	SE + Predict > Observe	*d* = 0.97
Griffin et al. (2008)	College students	Read natural and social sciences text	SE text > Read-once SE text > Read-twice	*d* = 0.95 *d* = 0.63
Pine & Messer (2000)	Children (5–9-year-olds)	Solve balance beam task	SE expert > Observe	*d* = 0.61
Pillow et al. (2002)	Children (4–5-year-olds)	Predict misinterpretations	SE own > Observe SE puppet > Observe	*d* = 0.46 *d* = 0.73
			Mean Effect Size	*d* = 0.78

Self-Explanation versus Active Learning Activities

An active learning strategy is an activity that asks the learner to become physically involved in some activity so that it engages the learner's attention but does not require the learner to generate any additional output than that provided to the learner. The difference between active and constructive learning activities is whether or not the learner produced additional information. Learning is expected to be greater when a student is engaged in a constructive activity and thus generating their own additional knowledge compared to learning in an active activity where the student is focused and engaged but does not produce any additional output. The following five studies represent an illustrative sample of the studies in the literature comparing self-explanation with a variety of active learning tasks, perhaps the most popular comparison found in the literature.

In the de Bruin et al. (2007) study described above, they compared learning outcomes for a group instructed to predict the next chess move of a computer opponent and explain why (self-explain + predict group) with a group instructed only to predict the next move (predict group). The self-explain + predict group provides an excellent example of a constructive activity compared with an active activity (predicting the next move). Predicting the next move can be categorized as active and not constructive since the subjects had been exposed to many possible computer moves in the learning phase and therefore were basically selecting the next move since they did not have to generate any novel moves. The researchers found that the self-explain + predict condition performed significantly better than the predict condition. For example, when compared with the predict group, the self-explain + predict group showed higher percentages of correct predictions (M = 66%, SD = 8.7 versus M = 59%, SD = 9.2), correct applications of chess principles (M = 63%, SD = 10.5 versus M = 50%, SD = 10.6), and a higher number of checkmates in the test phase (M = 3.0, SD = 1.77 versus M = 0.87, SD = 0.92 with a very large effect size of d = 1.51).

In an investigation of problem-solving skills, Aleven and Koedinger (2002) compared two different versions of a computer-based tutoring program on problem-solving and transfer outcome measures for tenth grade high school geometry students. The self-explain + solve group was prompted to solve the geometry problem and required to type a reason for their solution. This activity would be classified as a constructive learning activity due to the fact that the students had to generate new output via their self-explanations. The solve group was prompted to solve the geometry problem but was not required to enter a reason for their answer. This was the only difference between the two groups. The solve group would be considered active since the students engaged in a physical activity of generating steps that they had seen before but they did not have to produce output that contained ideas going beyond the information presented. Since feedback was comparable across both conditions, we can hold the feedback as a constant and compare the constructive versus the active nature of the student activities as opposed to the interactive aspect of the Intelligent Tutoring System. The researchers found that students in the self-explain + solve group improved significantly more that those in the solve condition in all three post-test measures, $F(1,22) = 10.3$, $p < 0.005$, with a very large effect size of $d = 1.37$.

Kastens and Liben (2007) examined spatial task abilities of fourth graders by requiring them to place stickers on a map corresponding to the real-world locations of flags placed around an outdoor park area. The researchers divided the children into two groups. One group was given a map and told to explore the area and place stickers on the map corresponding to the flag locations as they discovered them (place-sticker group). This task clearly qualifies as an active learning activity as the children are so obviously engaged in doing something physical (i.e., exploring the park area and physically placing the stickers on the map) but are not required to generate any novel output. The second group of children received the exact same instructions as the first group with one modification. The students in the second group were told that after they found the flag and placed their sticker on the map, they were to write down the clues they had used to decide where to place the sticker on the map (self-explain + place-sticker group). This group constitutes the self-explanation group and the fact that they generated additional output than that provided to them originally (specifically, their explanations as to sticker placement) places this learning task in the constructive category. As predicted by the passive-active-constructive-interactive framework, the self-explanation group performed significantly better than the active group who placed the stickers on their maps without explanation. The main measure of learning was how far off the sticker was placed from the true location on the map, measured in units of sticker diameter. This measure was called the sticker offset and the researchers found an average sticker offset of 4.9 ($SD = 3.1$) in the active learning condition and only 2.2 ($SD = 1.5$) in the constructive, self-explanation condition, $F(1,29) = 23.20$, $p < 0.001$, $d = 0.96$.

O'Reilly, Symons, and MacLatchy-Gaudet (1998) tested college students' recall and recognition ability for factual knowledge of the human circulatory system under three different learning conditions: repetition, elaborative interrogation, and self-explanation. For the purposes of the comparisons in this section of the chapter, we will examine the repetition and the self-explanation groups. Although the researchers did not record or analyze the subjects' verbal protocol, the two learning strategies can be categorized within the passive-active-constructive-interactive framework by examining the overt activities the subjects were instructed to engage in. The prompt for the repetition group was to "repeat each sentence until the next fact appears on the computer screen" thus placing this group in the active learning category. The self-explanation group was prompted with the instructions, "Explain what the sentence means to you. That is, what new information does the sentence provide for you? And how does it relate to what you already know?" This activity requires the subject to generate additional output and places the self-explanation condition into a constructive learning activity. As predicted, the researchers found that cued recall and recognition were higher for the self-explanation group ($M = 18.36$, $SD = 5.21$) when compared to the repetition group ($M = 14.04$, $SD = 4.46$), $F(2, 52) = 4.89$, $p < 0.05$, $d = 0.92$.

In a study by King (1992), learning outcomes were compared across three groups of underprepared college students. The students were trained in techniques of self-questioning, summarizing, or note-taking and presented with a traditional lecture. Learning was measured after the lecture through assessments of comprehension, retention, and idea units listed in the students' lecture notes. The self-questioning group can be classified as self-explaining and thus constructive on the basis of the prompts used to guide the student learning strategy. The prompts for the self-questioning group included statements such as "What is the main idea of . . .?", "How does . . . relate to . . .?", and "What conclusions can I draw about . . .?" Previous studies on self-questioning have proposed that such prompts facilitate learning by inducing cognitive activities including the integration of new information with existing knowledge (Palincsar & Brown, 1984).

In essence, the self-questioning group is being taught to self-explain through the use of generic question-stem prompts. After being trained with the question-stem prompts, the students in the self-questioning group then generated and answered their own questions, thus providing explanations for their self-generated prompts. The summarizing group is discussed in the next section of this chapter. The third group of students was instructed to simply take notes during the lecture and, assuming that student notes tend to be verbatim copying, can thus be classified as an active learning strategy at best. The researchers found that the constructive activity of self-explaining was superior to the active learning task of note-taking for retention (M = 51.05, SD = 12.87 versus M = 33.88, SD = 19.75), comprehension (M = 67.74, SD = 11.16 versus M = 59.90, SD = 12.06), and number of important idea units in the post-test lecture notes (M = 17.70, SD = 4.80 versus M = 13.30, SD = 4.80, with a large effect size of d = 0.92).

As can be seen in all five studies described above, the constructive strategy of self-explanation consistently results in higher learning outcomes when compared with a diverse set of active learning activities commonly used in the classroom. Table 15.3 summarizes the five studies described in this section and illustrates the advantages of self-explanation over a variety of active activities with an overall mean effect size of d = 1.14.

Self-Explanation versus Other Constructive Learning Activities

According to the passive-active-constructive-interactive framework, a comparison of self-explanation with other constructive types of learning strategies should result in similar learning outcomes since one constructive learning activity should not in principle be better than another constructive learning activity. Surprisingly, there are relatively few experimental studies comparing self-explanation with alternative constructive activities. The most commonly used constructive activities in addition to self-explanation include compare-and-contrast, concept mapping, drawing diagrams, and generative summarizing. The following two studies provide an illustration of equivalent learning outcomes between two constructive activities.

In the King (1992) study cited in the section above in which she compared learning outcomes across three groups of underprepared college students, the self-questioning group, the generative summary group, and the note-taking group, we had determined that the self-questioning group is essentially a self-explanation group. The generative summary group was trained to create what King referred to as a generative summary as opposed to the select-delete-modify approach that many students commonly use when attempting to summarize a lecture or text. The students in the generative summary group were trained to use their own words to construct novel sentences that make connections between the existing material and the students' own prior knowledge. Assuming that the students were able to implement the training correctly, this activity would be classified as a constructive learning activity and thus this study provides a direct comparison between two different constructive learning activities.

Table 15.3 Summary of studies: self-explaining (SE) versus active

Study	Age Group	Text/Task	Results	Effect Size
De Bruin et al. (2007)	College students	Predict computer chess move	SE + Predict > Predict	*d* = 1.51
Aleven & Koedinger (2002)	Adolescents (tenth graders)	Solve math problems with computer tutor	SE + Solve > Solve	*d* = 1.37
Kastens & Liben (2007)	Children (fourth graders)	Place stickers on field map	SE + Place-sticker > Place-sticker	*d* = 0.96
O'Reilly et al. (1998)	College students	Read circulatory system text	SE > Repeat Sentence	*d* = 0.92
King (1992)	College students	Listen to a lecture	SE > Take notes	*d* = 0.92
			Mean Effect Size	*d* = 1.14

The third group was instructed to simply take notes during the lecture and as described in the preceding section, can be classified as an active learning strategy at best. As predicted by our hypothesis, there were no significant differences found between the self-explanation group and the generative summary group in lecture comprehension (M = 67.74, SD = 11.16 versus M = 74.68, SD = 9.41, respectively) or retention (M = 51.05, SD = 12.87 versus M = 44.74, SD = 25.25, respectively). In addition, no significant differences were found between the self-explanation group and the generative summary group in the deeper learning measure of percentage of important idea units in the post-test lecture notes (M = 17.7%, SD = 4.8 versus M = 17.2%, SD = 5.2 with a negligible effect size of d = 0.10).

The Pillow et al. (2002) study described in a preceding section and shown in Table 15.2, also compared two conditions that were both constructive. Recall that their task was to investigate the effects of explanation on 4- and 5-year-olds' ability to predict misinterpretations of ambiguous pictures. The first condition prompted the children to explain their own misinterpretations (self-explain own), the second condition prompted the children to explain the misinterpretations of a puppet viewing similar drawings (self-explain puppet), and the third condition instructed the children to simply view the drawings while the experimenter discussed the drawings (observe). The first training condition falls under the realm of self-explanation and should be classified as a constructive activity since the children were required to produce output beyond that provided to them. The second condition, explaining someone else's misinterpretation (in this case, a puppet), also falls under the category of constructive since the children once again had to generate novel output to complete the task. The final group required no action or output on the part of the children, that makes it a passive activity and has already been discussed earlier and shown in Table 15.2. We would anticipate that learning outcomes between the first two training conditions would be fairly equivalent since they both fall into the constructive category. The researchers' findings were as anticipated with no significant differences between the two explanation conditions. For example, the 5-year-olds in the self-explain own group scored an average of 65% correct (SD = 33.6%) on the think-reality contrast questions in the study compared to 79% correct (SD = 45%) for the self-explain puppet group on the same task. The difference between the conditions was not significant, F(1, 85) = 0.02 with a small effect size of d = 0.35.

Although the passive-active-constructive-interactive framework predicts equivalent learning outcomes between two constructive learning activities, surprisingly, three of the five studies we examined yielded significantly higher learning outcomes for the self-explanation condition when compared to other constructive learning activities. For example, a study by Roscoe and Chi (2008) clearly illustrates the superiority of self-explanation as a constructive learning activity. In that study, college undergraduates were asked to read a text on the human eye and retina and then were assigned to one of three experimental conditions. The first group was given 30 minutes to explain the text to a peer tutee (explain-to-other group), the second group was given 30 minutes to create a tutorial videotape about the text that would be shown to a future student (explain-to-video group), and the third group was given 30 minutes to review the text and explain aloud to themselves as they read (self-explain text group). All groups were encouraged to “go beyond what the text says.” The first (explain-to-other) condition falls into the category of interactive and will be discussed in the next section.

On the surface, it appears that the last two conditions (explain-to-video and self-explain text) would both satisfy the criteria of the constructive category as it seems that the subjects produced additional novel output. We would predict that the two conditions would produce similar learning outcomes, however, the researchers found that the self-explainers seemed to gain a deeper understanding of the material than the tutorial (explain-to-video) explainers. For example, post-test scores on the questions test (a measure of deeper learning than the definitions test given in the study) found that the self-explain text group had a mean score of 32.4 (SD = 4.9) while the explain-to-video group showed a mean score of only 24.1 (SD = 5.3). This difference was significant with a large effect size of d = 1.64. A closer analysis can provide some insight into the advantages gained by the self-explanation condition.

A detailed protocol analysis was conducted for each condition examining the types of activities in which the subjects engaged. The researchers found that if the activities were broken down into knowledge-telling versus knowledge-building activities, then the explain-to-video group engaged in a significantly higher proportion of knowledge-telling episodes (M = 0.87, SD = 0.11) than the self-explain text group (M = 0.60, SD = 0.16). On the other hand, the self-explain text group engaged in almost four times as many knowledge-building episodes as the explain-to-video group (M = 13.6, SD = 5.1 compared to M = 3.7, SD = 3.3). Knowledge-telling activities consisted primarily of paraphrase statements and were essentially unelaborated summaries of the text while knowledge-building activities were defined as verbal episodes involving the integration of concepts and the generation of knowledge through inferences (Scardamalia & Bereiter, 1994). In other words, knowledge-telling episodes included active learning activities while knowledge-building required constructive activity on the part of the learner. Thus, the fact that the self-explain text group outperformed the explain-to-video group is consistent with the prediction of our framework and may be attributed to the greater degree of inference generation and knowledge integration observed in the self-explain text condition. The question remains as to why the self-explain group was more likely to engage in knowledge-building than knowledge-telling.

In addition to the Roscoe and Chi (2008) findings just described, several researchers have found a clear advantage for one type of self-explain condition when compared to an alternative self-explain group. Siegler (1995) asked 5-year-old children to participate in a Piagetian number conservation task under one of three different conditions. The control group simply performed the task and was given feedback on the correctness of their answer (solve group), the second group performed the task, was asked to explain how they knew that was the answer and were then given feedback on the correctness of their own answer (self-explain own + solve group), and finally, the third group performed the task, was given feedback on the correctness of their answer and then was asked to explain how the researcher knew that was the correct answer (self-explain expert + solve group).

The researchers found that the self-explain expert group displayed a significantly higher percentage of correct answers (*M* = 62%) when compared to the self-explain own group (*M* = 48%). This difference was significant, however, not enough data were presented in the article to estimate effect size. Since self-explain own and self-explain expert seem to be the only activity that differed between the second and third condition, and since both activities (self-explain self and self-explain expert) appear to fall under the category of constructive, a closer examination of the children's verbal protocols is required in order to understand the differential learning outcomes.

One interpretation is that self-explaining an expert's solution is analogous to the traditional self-explaining a text condition wherein the text contains correct information. In this case, the contrast is between self-explaining an expert's correct solution versus one's own imperfect solution. It is not surprising that one might learn more information from a correct solution. Moreover, it turns out that Siegler (1995) found the self-explain expert group to be engaged in generating a greater number of explanations and also generated a greater diversity of explanation types. We know that the number of self-explanations generated typically predicts the amount of learning (Chi et al., 1994).

To further examine the difference between a self-explain own versus a self-explain expert condition, a study by Calin-Jageman and Ratner (2005) instructed children to solve addition problems and after receiving feedback on the correct answer, they were asked to explain "How did I [the researcher] know that?" (self-explain expert group) or "How did you know that?" (self-explain own group). Again, the researchers found that the self-explain expert group displayed significantly more improvement in their scores than the self-explain own group and was much more likely to use the strategy of the researcher (i.e., "count-all strategy") than the self-explain own condition as revealed through the degree to which they encoded the expert's behavior, referred to as the "encoding score" and measured in the last testing session. The self-explain expert group had an average encoding score of 1.67 (*SD* = 0.90) while the self-explain own group had an average encoding score of only 0.89 (*SD* = 0.90). This difference was significant with a large effect size of *d* = 0.87. An analysis of the types of explanations provided between the two groups showed that the self-explain expert group produced significantly more "what + why" explanations versus the simple "what" explanations provided by the self-explain own group. Again, generating more "what + why" explanations indicate that the self-explain expert condition led to more constructive activity on the part of the children. Of course we still need to understand why self-explain expert leads to the generation of more "what + why" explanations.

In summary, two of the five studies described above found no differences between learning outcomes in a self-explanation condition compared to an alternative constructive activity, as predicted by our theoretical framework. The overall mean effect size for the studies with equivalent learning outcomes was small with *d* = 0.23. Surprisingly, three of the five studies comparing self-explanation to other constructive learning activities resulted in superior learning outcomes among the self-explanation groups when compared to alternative constructive activities, with a large effect size, *d* = 1.26. Since the passive-active-constructive-interactive framework predicted equivalent results, obtaining non-equivalent learning results needs to be accounted for by the specific task demands of the contrasting constructive activities.

A variety of reasons in the task demands could account for the superior learning outcomes of the self-explaining group (including self-explaining a text, or self-explaining an expert's solution), such as more knowledge-building activities in a self-explain versus explain-to-a-video group, and an increased generative activity of the subjects in the self-explain expert conditions when compared to the self-explain own condition. However, additional explanations need to be provided for why self-explaining has more favorable task demands than other constructive activities. For example, why does self-explaining generate more knowledge-building than explaining-to-a-video? One post-hoc explanation is that explaining-to-a-video is like teaching to an audience, in which a teacher prefers to explain what she or he already knows, thus restricting what she or he can learn from explaining. Similar other post-hoc explanations can be given for why self-explaining expert is superior to self-explaining own. One reason is that an expert's solution contains more correct information; therefore explaining a correct solution allows one to learn more than explaining one's own erroneous solution. Therefore, although self-explaining should in principle produce equivalent learning outcomes as other constructive learning activities, the task demands of self-explaining show it often to be a superior constructive activity as compared with others. A summary of the findings from this section can be found in Table 15.4.

Self-Explanation versus Interactive Learning Activities

From a learning perspective, the critical components of interactive situations beyond the advantage of construction, is receiving additional information in the form of feedback, elaborations, questions, and so forth. Our framework predicts that interactive activities should, in general, lead to better learning outcomes than the constructive activity of self-explaining. However, it will be important to examine the precise nature of the interactions as they can vary in degree of exchanges as well as the level of constructive engagement. Most of the studies comparing self-explanation to an interactive learning condition are fairly recent. We have selected five studies to demonstrate this contrast below.

One of the clearest comparisons between the individual constructive activity of self-explanation and an interactive learning task can be found in a study conducted by Hausmann, van de Sande, and VanLehn (2008). College students were assigned the task of alternating between solving physics problems with the aid of a computer-based intelligent tutoring program and explaining worked-out physics problems presented by the tutoring program in video format. The researchers divided the students into two groups. In the self-explain group, students worked alone at the computer to solve the problems and were prompted to generate explanations to the solution steps presented in the video examples. In the joint-explain group, students worked in dyads at the computer to solve the physics problems and then generated joint explanations to the video presented solution steps. The critical difference between the two conditions is whether the individual was working alone or with a partner. The results of the study clearly show the advantages of an interactive environment. The dyads answered faster, finished more problems in the allotted time, entered more correct entries, displayed a lower error rate and requested fewer hints when solving problems in the computer program. Specifically, on one measure of learning outcome, the individuals requested an average of 2.26 hints (SD = 1.52) while the dyads requested an average of only 0.99 hints (SD = 0.82). Requesting more hints means the individuals cannot figure out how to solve the problem, therefore they needed more help as provided in the hints. This difference was statistically significant with a large effect size, d = −1.13. We report the effect size as negative because of the direction of the comparison, in that self-explaining condition was worse than the joint-explaining condition. While both conditions engaged in the constructive task of explaining, the results clearly show the advantage of interactions over working alone.

Table 15.4 Summary of studies: self-explaining (SE) versus constructive

Study	Age group	Text/task	Results	Effect size
King (1992)	College students	Listen to a lecture	SE lecture = Generative summary	d = 0.10
Pillow et al. (2002)	Children (4–5-year-olds)	Predict misinterpretations	SE own = SE puppet	d = 0.35
			Mean Effect Size	d = 0.23
Roscoe & Chi (2008)	College students	Read a text on the human eye	SE text > Explain-to-video	d = 1.64
Siegler (1995)	Children (5-year-olds)	Solve a number conservation task	SE expert + solve > SE own + solve	d = *
Calin-Jageman & Ratner (2005)	Children (5-year-olds)	Solve addition problems	SE expert > SE own	d = 0.87
			Mean Effect Size	d = 1.26
Note: * Not enough data provided to calculate effect size.				

To illustrate the importance of the nature of the interactive activity on learning outcomes, Kramarski and Dudai (2009) assigned one hundred ninth grade students to one of three instructional conditions. In the first two conditions, the students worked in groups of four to solve mathematical problems at a computer screen. The students solved the problems individually and interacted with the others in their group via an online forum. The self-explain own group was trained to generate self-explanations to prompts such as "What is my conclusion?" and "Is my explanation clear?" as they solved math problems. The feedback group was trained to generate explanations utilizing prompts that focused on responding to the other members' contributions, such as "How can I respond to my friend regarding the correctness of his/her explanation?" and "How can I modify my friend's solution and explanation?" A third control group did not receive any training on using prompts while solving the math problems. The level of interaction should be highest among the feedback group and, based on our theoretical framework, we would expect this group to demonstrate the highest learning gains. In fact, the researchers did find that the feedback group scored significantly higher in their mathematical accuracy than the self-explain own group and also scored higher in the deeper measure of problem-solving transfer scores (M = 86.43, SD = 19.9 for feedback group versus M = 71.39, SD = 26.20 for self-explain own group) with a medium effect size of d = −0.65.

In another study demonstrating the advantages of an interactive learning activity over an individual constructive learning task, Coleman, Brown, and Rivkin (1997) assigned college undergraduates to two different interactive conditions and compared the learning outcomes with a group of undergraduates assigned to a constructive self-explain condition. The students in the two interactive groups were instructed to study a text on natural selection and to either teach the contents through explanation (explain-to-other) or through summary to their partners (summarize-to-other). The self-explanation group was instructed to study the same material and explain the material aloud to themselves (self-explain text).

As predicted, the researchers found that both interactive conditions (explain-to-other and summarize-to-other) outperformed the constructive activity of self-explanation, F (2, 77) = 9.74, p < 0.001. For example, the explain-to-other and summarize-to-other conditions scored an average of 7.36 (SD = 0.44) and 7.07

($SD = 0.44$) respectively on a near-transfer task, while the self-explain text condition only scored an average of 6.78 ($SD = 0.44$) on the same task. This difference was significant with small effect sizes of $d = -0.35$ and $d = -0.18$ respectively. These results are consistent with our hypothesis that interactive learning activities should yield greater learning outcomes than constructive activities.

The three studies described in this section so far have demonstrated that the constructive activity of self-explaining is worse than interactive learning activities, with the interactive learning activity having an overall clear advantage with an effect size of $d = -0.58$. However, not all studies have followed our predicted direction and these studies need to be examined more closely to understand why. The two following studies illustrate our point. Moreno (2009) investigated whether college undergraduates engaged in two types of interactions (cooperative or jigsaw) would learn more than students working alone using a self-explanation technique. The students worked with an agent-based computer instructional program to learn about botany. The cooperative condition consisted of students working together at the computer throughout the entire learning phase to solve the problems as a team while the jigsaw condition involved each student working individually at the computer to learn their piece of the material and then coming back together as a group to teach each other what they had learned individually. The self-explanation condition consisted of students working alone at the computer and then after finishing their tasks with the computer program, generating self-explanations to the solutions they had produced earlier.

Looking only at the more important deep learning measures of a problem-solving transfer test, Moreno found no differences between the self-explanation ($M = 17.7$, $SD = 4.05$) and the cooperative groups ($M = 18.7$, $SD = 3.84$), $d = 0.25$, but a significant advantage of the self-explanation group compared to the jigsaw group ($M = 15.11$, $SD = 3.81$), with a medium effect size of $d = 0.66$.

These findings at first seem surprising as they contradict our prediction, since both jigsaw and cooperative activities would seem to fit into the interactive category while self-explanation is clearly constructive. A more detailed analysis of the methodology is required to understand the apparent contradictions. First, we would expect that the cooperative (interactive) group would score higher than the self-explanation (constructive) group, however, no significant differences in transfer scores were found. One possible explanation for the null finding is that the self-explanation group actually had the benefit of additional information over the cooperative group. At the end of the computer program session, the self-explanation group was given a four-page review sheet to facilitate the generation of self-explanations. In addition, although the self-explanation group did work individually on the learning task, the agent-based computer program provided feedback to both the cooperative and self-explanation group. This human–computer interaction could have strengthened learning in the self-explanation group and helped contribute to the null results between the cooperative and self-explanation learning strategies.

The second finding is even more surprising in that the constructive activity of self-explanation was actually superior to the interactive jigsaw condition. If we look only at the learning phase of the study, the cooperative group learned in pairs, while both the jigsaw and the self-explanation group learned alone. In this way, the jigsaw group was not interactive in the learning phase and was not even constructive, but was merely active because the students were not required to generate any novel output as they worked through the computer program alone. Thus, it makes sense that this active learning condition did not score higher than the constructive activity of self-explanation. Another way to show that the jigsaw group may have only been active is that the jigsaw group made a significantly higher proportion of retention statements than the cooperative group ($M = 0.68$, $SD = 0.10$ versus $M = 0.56$, $SD = 0.06$, respectively). Retention statements represent a knowledge-telling approach to teaching a peer or explaining a concept and do not require the generation of any new novel output, suggesting that the jigsaw group was engaged only in a more active type of interaction in which they were involved in a physical activity but were not producing any novel output. Thus, if the jigsaw group was only active, then it makes sense that they learned less than the self-explaining constructive group.

A similar result to the study described above was found by Roscoe and Chi (2008) comparing the effects of peer tutoring with self-explanation. The study, described in a previous section of this chapter, consisted of giving college undergraduates a text to learn about the human eye and then instructing them to either teach the information to a peer tutee (explain-to-other), teach the information to a video (explain-to-video), or self-explain the information to themselves (self-explain text). Contrast between the latter two groups was reported in Table 15.4. Here, an examination of the first and last groups allows a comparison between an interactive condition (explain-to-other) and a constructive self-explanation condition (self-explain text). Both groups were instructed to "go beyond what the text says" and thus were encouraged to engage in constructive activities either alone (self-explain text group) or with a partner (explain-to-other group). The researchers found no difference between the two groups on a shallow definitions post-test (M = 37.6, SD = 11.4 for self-explanation, and M = 33.3, SD = 10.2 for explain-to-other). However there was a significant difference in the deeper learning outcome of a questions post-test and unexpectedly, the self-explain text group performed better than the explain-to-other group (M = 32.4, SD = 4.9 versus M = 26.9, SD = 4.9. respectively). The difference between the groups was significant with a large effect size, d = 1.13. An examination of the verbal protocols reveals one possible explanation for this apparent discrepancy.

We expected that an interactive learning activity should yield greater learning outcomes than a constructive learning. Looking at the articulations of the subjects in the explain-to-other group, it can be seen that the subjects were engaged in some constructive activity (for example, 28% of their statement episodes consisted of knowledge-building, a constructive type of activity), however, they were primarily engaged in the more active task of knowledge-telling. This type of activity made up 72% of their verbal interactions. On the other hand, an investigation of the statements made by the self-explain group revealed that this group spent 40% of their time in the constructive task of knowledge-building and only 60% of their time engaged in knowledge-telling activities. One explanation for why students engaged mostly in knowledge-telling when they are teaching a peer is that the explainers tend to teach only what they already know. Thus, they are basically regurgitating existing knowledge instead of being constructive by building new knowledge. It seems that one goal in designing an effective interactive learning situation is to ensure that the students engage in constructive and not merely active tasks during their interactions together.

In summary, in comparing interactive tasks with self-explaining, four comparison conditions in three of the five studies presented found that the interactive condition resulted in significantly greater learning gains, with an average effect size of d = −0.58, as predicted by our theoretical framework. Two other studies actually found self-explaining (a constructive activity) to be as good as or better than interactive activities. We surmise that the task demands of self-explaining led to studies with mixed or equivalent outcomes. Table 15.5 provides a summary of the results described in this section.

DISCUSSION AND PRACTICAL IMPLICATIONS

The illustrative examples presented in the preceding sections provide strong support for a passive-active-constructive-interactive theoretical framework for learning strategies. It is hoped that such comparisons will not only help to simplify the numerous studies conducted to date on self-explanations, but also help to guide future research on the effectiveness and implementation of self-explanation to aid learners' success. Comparisons between self-explanation and passive learning activities consistently showed that self-explanation, as a constructive strategy, led to greater learning outcomes, especially when looking at measures of deep learning. The overall average effect size was large with d = 0.78. In addition, an overview of research studies comparing active learning activities with self-explanation also consistently showed greater learning gains among the self-explanation experimental groups, with a very large overall average effect size of d = 1.14.

As expected, for two of the studies, the comparisons among self-explanations and other constructive activities found no differences and showed a small overall average effect size of d = 0.23. However, for three of the five studies reviewed, self-explaining was actually superior, with an average effect size of d = 1.26.

Table 15.5 Summary of studies: self-explaining (SE) versus interactive

Study	Age group	Text/task	Results	Effect size
Hausmann, van de Sande, & VanLehn (2008)	College students	Solve physics problems	SE < Joint-explain	d = −1.13
Kramarski & Dudai (2009)	Adolescents (ninth graders)	Solve math problems	SE own < Feedback	d = −0.65
Coleman et al. (1997)	College students	Read a text on natural selection	SE text < Explain-to-other SE text < Summarize-to-other	d = −0.35 d = −0.18
			Mean Effect Size	d = −0.58
Moreno (2009)	College students	Interact with computer botany program	SE = Cooperative group SE > Jigsaw group	d = 0.25 d = 0.66
Roscoe & Chi (2008)	College students	Read a text on the human eye	SE text > Explain-to-other	d = 1.13

When the comparisons did not yield the predicted equivalent outcomes, more detailed analyses of the research designs and of the subject verbal protocols, when available, allowed us to identify the probable explanations of the findings within the theoretical framework of our hypothesis. The unexpected results were explained based on factors such as task demands and methodological design that either encouraged or suppressed explanations. For example, self-explaining a correct solution or a correct text was often better than explaining-to-video or explaining one's own incorrect solution because feedback is provided in self-explaining a correct solution or text. Similarly, although we expected self-explaining to be inferior to interactive activities that benefitted from additional information (e.g., feedback, elaborations, questions, etc.), the difference was not as large as might be expected, with an overall average effect size of d = 0.58. Moreover, we found mixed results among the comparisons of other self-explanation studies and interactive learning activities. However, again these findings could be fairly easily resolved to understand why they were not in the predicted direction, via a more thorough examination of the methods and results and in particular, by looking more closely at the precise nature of the interaction.

Overall, we can conclude that self-explaining consistently led to higher learning gains when compared to passive or active tasks. Among the five studies that contrasted self-explaining with other constructive tasks, self-explaining yielded equivalent or superior learning gains in all five of the studies. Finally, we predicted that self-explaining, being a constructive activity, ought to be consistently worse than other interactive activities and found that to be the case in four comparison conditions among three of the five studies. Surprisingly, self-explaining was equal or better than interactive activities in two of the studies, perhaps due to the fact that self-explaining is inherently constructive in nature, while the level of constructive engagement varies in an interactive learning environment depending on the nature of the task.

What are the practical implications for such findings in the actual classroom and even if self-explanation is the better technique in the research environment, is it always the best choice for the classroom? As an instructor, perhaps the most straightforward implementation to make in the classroom is to move across the categories of our theoretical framework. That is to say, for example, to take an activity from an active format into a constructive format. For instance, instead of having students underline a text (active), ask the students to generate explanations for each idea unit (constructive). Or, for example, instead of asking students to read aloud (active), have them engage in a "questioning the author" (constructive) activity (McKeown & Beck, 1999). Even moving from passive to active should increase learning gains for the student and should be fairly easy to implement on a daily basis. The greatest success will most likely come from picking activities that are more active, constructive, or interactive in nature and that are also easy to implement.

A more challenging task is selecting the right activity within a specific category. For example, even if self-explanation is superior in a research study, other constructive activities might be more straightforward to implement for both the students and the teacher, such as, for example, compare and contrast or concept-mapping. Again, in practical terms, the most important deciding factor is most likely the ease of implementation in the actual classroom.

FUTURE DIRECTIONS

An interesting direction for the implementation of our theoretical framework is in the area of online learning. The computer–student relationship of any online class is inherently interactive, but that does not necessarily make the student activity itself interactive. A student could easily sit in front of a computer and engage in a passive learning activity such as reading a text. This is commonly seen in many online learning classes. An opportunity exists to move the student–computer interaction to a more active, constructive or interactive level. For example, instead of just having the student read a text for an online class, ask the student to underline key words (active) or explain key concepts when given a prompt (constructive) or generate joint explanations with another student in a web-based chat situation (interactive). It is the responsibility of the instructor to structure the student–computer interaction in a way that maximizes learning outcomes. Instructors and researchers both need to look at what the student is doing—is it passive (just reading on the text screen), active (e.g., clicking on pages, opening and playing videos), or constructive (e.g., generating novel output through compare/contrast, generative summaries, self-explanations, and creating concept maps)? And if the experience is supposed to be an interactive one, then it is important to make sure that the interactions are not empty, in that the students are in fact making substantive contributions and experiencing true interactions in terms of receiving and providing feedback, defending and challenging positions, and so forth. Other motivational factors, such as the presence or absence of an on-screen agent, may also need to be considered in order to design the most effective future learning environments in the ever-increasing online learning community.

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REFERENCES

- Ainsworth, S., & Burcham, S. (2007). The impact of text coherence on learning by self-explanation. Learning and Instruction, 17, 286-303.
- Ainsworth, S., & Loizou, A. T. (2003). The effects of self-explaining when learning with text or diagrams. Cognitive Science: A Multidisciplinary Journal, 27(4), 669-681.
- Aleven, V. A. W. M. M., & Koedinger, K. R. (2002). An effective metacognitive strategy: Learning by doing and explaining with a computer-based Cognitive Tutor. Cognitive Science, 26(2), 147-179.
- Bielaczyc, K., Pirolli, P. L., & Brown, A. L. (1995). Training in self-explanation and self-regulation strategies: Investigating the effects of knowledge acquisition activities on problem solving. Cognition and Instruction, 13(2), 221-252.
- Butcher, K. R. (2006). Learning from text with diagrams: Promoting mental model development and inference generation. Journal of Educational Psychology, 98(1), 182-197.
- Calin-Jageman, R. J., & Ratner, H. H. (2005). The role of encoding in the self-explanation effect. Cognition and Instruction, 23(4), 523-543.
- Chi, M. T. H. (2000). Self-explaining expository texts: The dual processes of generating inferences and repairing mental models. In Glaser, R. (Ed.). Advances in Instructional Psychology (pp. 161-238). Mahwah, NJ: Lawrence Erlbaum Associates.
- Chi, M. T. H. (2009). Active-constructive-interactive: A conceptual framework for differentiating learning activities. Topics in Cognitive Science, 1, 73-105.
- Chi, M. T. H., Bassok, M., Lewis, M., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. Cognitive Science, 13, 145-182.
- Chi, M. T. H., de Leeuw, N., Chiu, M., & LaVancher, C. (1994). Eliciting self-explanations improves understanding. Cognitive Science, 18, 439-477.
- Chi, M. T. H., Lewis, M. W., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. Cognitive Science, 13, 145-182.
- Cohen, J. (1992). A power primer. Psychological Bulletin, 112, 155-159.
- Coleman, E. B., Brown, A. L., & Rivkin, I. D. (1997). The effect of instructional explanations on learning from scientific texts. The Journal of the Learning Sciences, 6(4), 347-365.
- de Bruin, A., Rikers, R., & Schmidt, H. (2007). The effect of self-explanation and prediction on the development of principled understanding of chess in novices. Contemporary Educational Psychology, 32(2), 188-205.
- Ferguson-Hessler, M. G. M., & de Jong, T. (1990). Studying physics texts: Differences in study processes between good and poor performers. Cognition and Instruction, 7(1), 41-54.
- Griffin, T. D., Wiley, J., & Thiede, K. W. (2008). Individual differences, rereading, and self-explanation: Concurrent processing and cue validity as constraints on metacomprehension accuracy. Memory & Cognition, 36(1), 93-103.
- Hausmann, R. G. M., & Chi, M. T. H. (2002). Can a computer interface support self-explaining? Cognitive

Technology, 7(1), 4-14. E-JOURNAL PORTAL

- Hausmann, R. G., van de Sande, B., & VanLehn, K. (2008). Are self-explaining and coached problem solving more effective when done by pairs of students than alone? In Love, B. C., McRae, K., & Sloutsky, V. M. (Eds.), Proceedings of the 30th Annual Conference of the Cognitive Science Society. (pp. 2369-2374). New York: Erlbaum. E-JOURNAL PORTAL
- Kastens, K. A., & Liben, L. S. (2007). Eliciting self-explanations improves children's performance on a field-based map skills task. Cognition and Instruction, 25(1), 45-74. E-JOURNAL PORTAL
- King, A. (1992). Comparison of self-questioning, summarizing, and notetaking-review as strategies for learning from lectures. American Educational Research Journal, 29(2), 303-323. E-JOURNAL PORTAL
- Kramarski, B., & Dudai, V. (2009). Group-metacognitive support for online inquiry in mathematics with differential self-questioning. Journal of Educational Computing Research, 40(4), 377-404. E-JOURNAL PORTAL
- Mayer, R. E. (2008). Learning and instruction (2nd ed.). Upper Saddle River, NJ: Pearson Merrill Prentice Hall. E-JOURNAL PORTAL
- McKeown, M. G., & Beck, I. L. (1999). Getting the discussion started. Educational Leadership, 57, 25-28. E-JOURNAL PORTAL
- McNamara, D. S. (2004a). iSTART: Interactive strategy training for active reading and thinking. Behavior Research Methods, Instruments & Computers, 36(2), 222-233. E-JOURNAL PORTAL
- McNamara, D. S. (2004b). SERT: Self-explanation reading training. Discourse Processes, 38(1), 1-30. E-JOURNAL PORTAL
- McNamara, D. S., Levinstein, I. B., & Boonthum, C. (2003). iSTART: Interactive Strategy Trainer for Active Reading and Thinking. Behavioral Research Methods, Instruments, and Computers, 36, 222-233. E-JOURNAL PORTAL
- McNamara, D. S., O'Reilly, T. P., Best, R. M., & Ozuru, Y. (2006). Improving adolescent students' reading comprehension with iSTART. Journal of Educational Computing Research, 34(2), 147-171. E-JOURNAL PORTAL
- Moreno, R. (2009). Constructing knowledge with an agent-based instructional program: A comparison of cooperative and individual meaning making. Learning and Instruction, 19, 433-444. E-JOURNAL PORTAL
- Mwangi, W., & Sweller, J. (1998). Learning to solve compare word problems: The effect of example format and generating self-explanations. Cognition and Instruction, 16(2), 173-199. E-JOURNAL PORTAL
- Nathan, M. J., Mertz, K., & Ryan, R. (1994). Learning through self-explanation of mathematics examples: Effects of cognitive load. Paper presented at the annual meeting of the American Educational Research Association, New Orleans. E-JOURNAL PORTAL
- Neuman, Y., & Schwarz, B. (1998). Is self-explanation while solving problems helpful? The case of analogical problem-solving. British Journal of Educational Psychology, 68, 15-24. E-JOURNAL PORTAL
- O'Reilly, T., Symons, S., & MacLatchy-Gaudet, H. (1998). A comparison of self-explanation and elaborative interrogation. Contemporary Educational Psychology, 23, 434-445. E-JOURNAL PORTAL
- Palincsar, A. S., & Brown, A. L. (1984). Reciprocal teaching of comprehension fostering and comprehension monitoring activities. Cognition and Instruction, 1(2), 117-175. E-JOURNAL PORTAL
- Pillow, B. H., Mash, C., Aloian, S., & Hill, V. (2002). Facilitating children's understanding of misinterpretation: Explanatory efforts and improvements in perspective taking. The Journal of Genetic Psychology, 163(2) 133-148. E-JOURNAL PORTAL
- Pine, K. J., & Messer, D. J. (2000). The effect of explaining another's actions on children's implicit theories of balance. Cognition and Instruction, 18(1) 35-51. E-JOURNAL PORTAL
- Pirolli, P., & Recker, M. (1994). Learning strategies and transfer in the domain of programming. Cognition and Instruction, 12(3), 235-275. E-JOURNAL PORTAL
- Renkl, A. (1997). Learning from worked-out examples: A study on individual differences. Cognitive

Science: A Multidisciplinary Journal, 21(1), 1-29. E-JOURNAL PORTAL

- Renkl, A. (2002). Worked-out examples: Instructional explanations support learning by self-explanations. Learning and Instruction, 12(5), 529-556. E-JOURNAL PORTAL
- Renkl, A., Stark, R., Gruber, H., & Mandl, H. (1998). Learning from worked-out examples: The effects of example variability and elicited self-explanations. Contemporary Educational Psychology, 23, 90-108. E-JOURNAL PORTAL
- Roscoe, R. D., & Chi, M. T.H. (2008). Tutor learning: The role of explaining and responding to questions. Instructional Science, 36, 321-350. E-JOURNAL PORTAL
- Rosnow, R. L., & Rosenthal, R. (1996). Computing contrasts, effect sizes, and counternulls on other people's published data: General procedures for research consumers. Psychological Methods, 1, 331-340. E-JOURNAL PORTAL
- Scardamalia, M., & Bereiter, C. (1994). Computer support for knowledge building communities. Journal of the Learning Sciences, 3, 265-283. E-JOURNAL PORTAL
- Siegler, R. S. (1995). How does change occur?: A microgenetic study of number conservation. Cognitive Psychology, 28, 225-273. E-JOURNAL PORTAL
- Teasley, S. (1995). The role of talk in children's peer collaborations. Developmental Psychology, 31(2), 207-220. E-JOURNAL PORTAL
- Thalheimer, W., & Cook, S. (2002). How to calculate effect sizes from published research articles: A simplified methodology. Retrieved January 12, 2010 from http://work-learning.com/effect_sizes.htm. E-JOURNAL PORTAL
- Williams, J. J., & Lombrozo, T. (in press). The role of explanation in discovery and generalization: evidence from category learning. Cognitive Science. E-JOURNAL PORTAL
- Wong, R. M. F., Lawson, M. J., & Keeves, J. (2002). The effects of self-explanation training on students' problem solving in high-school mathematics. Learning and Instruction, 12, 233-262. E-JOURNAL PORTAL

Brenda A. Fonseca
Michelene T.H. Chi

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Fonseca, B. A., & Chi, M. T. (2011). Instruction based on self-explanation. In R. E. Mayer, & P. A. Alexander (Eds.), *Educational psychology handbook: handbook of research on learning and instruction*. London, UK: Routledge. Retrieved from https://login.ezproxy1.lib.asu.edu/login?url=https://search.credoreference.com/content/entry/routli/instruction_based_on_self_explanation/0?institutionId=2261

Chicago

Fonseca, Brenda A., and Michelene T.H. Chi. "Instruction Based on Self Explanation." In *Educational Psychology Handbook: Handbook of Research on Learning and Instruction*, edited by Richard E. Mayer, and Patricia A. Alexander. Routledge, 2011. https://login.ezproxy1.lib.asu.edu/login?url=https://search.credoreference.com/content/entry/routli/instruction_based_on_self_explanation/0?institutionId=2261

Harvard

Fonseca, B.A. and Chi, M.T. (2011). Instruction based on self-explanation. In R.E. Mayer & P.A. Alexander (Eds.), *Educational psychology handbook: handbook of research on learning and instruction*. [Online]. London: Routledge. Available from: https://login.ezproxy1.lib.asu.edu/login?url=https://search.credoreference.com/content/entry/routli/instruction_based_on_self_explanation/0?institutionId=2261 [Accessed 18 March 2019].

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Fonseca, Brenda A., and Michelene T.H. Chi. "Instruction Based on Self Explanation." *Educational Psychology Handbook: Handbook of Research on Learning and Instruction*, edited by Richard E. Mayer, and Patricia A. Alexander, Routledge, 1st edition, 2011. *Credo Reference*, https://login.ezproxy1.lib.asu.edu/login?url=https://search.credoreference.com/content/entry/routli/instruction_based_on_self_explanation/0?institutionId=2261. Accessed 18 Mar. 2019.