Transfer Effects of Prompted and Self-Reported Analogical Comparison and Self-Explanation

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Abstract

We compared types of transfer facilitated by instructions to engage in analogical comparison or self-explanation. Participants received learning materials and worked examples with prompts supporting analogical comparison, self-explanation, or instructional explanation study. Learners also self-reported their use of analogical comparison and self-explanation on a series of questionnaires. We evaluated condition effects on self-reports and transfer, and the relations between self-reports and transfer. Receiving materials with analogical-comparison support and reporting greater levels of analogical comparison were both associated with worse transfer performance, while reporting greater levels of self-explanation was associated with better performance. Learners' self-reports of analogical comparison and self-explanation were not related to condition assignment, suggesting that the questionnaires did not measure the same processes promoted by the intervention, or that individual differences are robust even when learners are instructed to engage in analogical comparison or self-explanation.

Keywords: analogical comparison; self-explanation; learning; transfer

Introduction

One goal of cognitive science is to examine the instructional techniques that support learning and transfer, or the application of knowledge to a new situation or problem. Analogical comparison and self-explanation are hypothesized to be two constructive, sense-making techniques for acquiring knowledge that transfers (Chi, 2009; Koedinger, Booth, & Klahr, 2013; Richey & Nokes-Malach, 2015), and both have shown consistent benefits for learning in the laboratory as well as the classroom. While they appear to rely on some of the same mechanisms (e.g., inference generation), they may also involve different mechanisms (e.g., mental model revision versus relational abstraction), and the exact nature of the knowledge acquired through each is not clear. Understanding differences in knowledge outcomes associated with each process has important implications for cognitive theory and instructional practice, particularly if there are instructional scenarios to which one approach is better suited than the other.

Little work has systematically compared the knowledge acquired through analogical comparison and self-explanation (cf. Edwards, 2014; Gadgil, Nokes-Malach, & Chi, 2012; Nokes-Malach, VanLehn, Belenky, Lichtenstein, & Cox, 2013), and the wide variety of tasks, scaffolding, and measurement employed in prior work make it difficult to compare experiments examining each process separately. Consequently, there is little evidence to suggest which process is most appropriate based on instructional goals (e.g., near or far transfer). We directly compare the two processes to identify differences, if any, in the knowledge representations acquired through each process.

It is also possible that instructions to engage in either analogical comparison or self-explanation promote use of both processes (Edwards, 2014). For example, comparisons often involve explicit explanations of features and their relations within examples, and explanation invites comparisons between prior knowledge and new information or different pieces of information. Thus, it is interesting to explore the degree to which students report engaging in both processes after receiving prompts for either self-explanation or analogical comparison. We investigate the relationship between instructional prompts, knowledge outcomes, and a new questionnaire measure targeting learners' self-reported use of self-explanation and analogical comparison.

Analogical comparison

Analogical comparison is an instructional technique in which learners receive multiple exemplars and engage in mapping features and relations between them, which leads to better encoding of abstract relations that can be applied to novel cases (Gentner, Loewenstein, & Thompson, 2003; Gick & Holyoak, 1983). Much prior research has shown that analogical comparison of examples can lead to generating inferences and encoding abstract information, which may make analogical comparison especially well-suited for supporting far transfer (Alfieri, Nokes-Malach, & Schunn, 2013). Because it emphasizes abstraction across examples and minimizes surface features, some evidence suggests it may not be as beneficial as other instruction, including self-explanation and worked-example study, for facilitating knowledge of specific problem-solving procedures (Nokes-Malach et al., 2013). Research has also shown a great deal of individual variability in the extent to which learners engage in analogical comparison, and learners sometimes fail to make fruitful comparisons across cases even when instructed to do so (Gick & Holyoak, 1983). Carefully selecting cases to highlight critical features and scaffolding comparison can improve outcomes (Gentner et al., 2003).

Developing an unobtrusive measure of analogical comparison suitable for use across a variety of academic settings could improve understanding of how frequently learners engage in it, and it could help explain why some students learn and transfer deep concepts more successfully than others. Prior work has assessed analogy use through verbal protocols (e.g., Richland, Holyoak, & Stigler, 2004) and experimental manipulations (e.g., Gick & Holyoak, 1983), but to our knowledge no work has related a multi-item questionnaire assessing students' use of analogical comparison to the effects of an instructional intervention.

Self-explanation

Self-explanation is another constructive instructional technique. Although it can take a variety of forms, two of the most fruitful types of self-explanation focus on filling in knowledge gaps through inference generation and revising errors in prior knowledge (Nokes, Hausmann, VanLehn, & Gershman, 2011). Self-explanation typically focuses on one example at a time and may better support encoding concrete problem features, which could result in better declarative memory of procedures. Self-explanation can support deep learning, conceptual change, and transfer, but like analogical comparison, there is much variability in volume and quality of self-explanations, whether they are spontaneous (Chi, Bassok, Lewis, Reimann, & Glaser, 1989) or prompted (Chi, Slotta, & de Leeuw, 1994). Additionally, the knowledge derived from self-explanation depends on both the content being explained and the types of explanations the learner generates, making self-explanation potentially more flexible than analogical comparison but perhaps also less structured.

Most studies of self-explanation involve extensive analysis of written or verbal protocols, constraining research to environments or tasks developed for the purpose of collecting protocols. A self-explanation questionnaire could be deployed more easily in a variety of academic settings and, similar to an analogical-comparison questionnaire, might improve understanding of why some students are more successful in acquiring concepts and revising misconceptions than others. Again, no work that we know of has attempted to relate an instructional intervention targeting self-explanation to self-reports on a multi-item self-explanation questionnaire.

The Present Study

Although analogical comparison and self-explanation are often studied separately, some recent work has compared the two (Edwards, 2014; Gadgil et al., 2012; Nokes-Malach et al., 2013). Gadgil et al. (2012) found that learners with misconceptions about the circulatory system were more likely to undergo conceptual change when they compared flawed mental models to an expert model, rather than self-explaining the expert model alone. This suggests analogical comparison can facilitate conceptual change, but it is not clear whether change was driven by analogical comparison or by drawing learners' attention to flawed mental models, which were not targeted for self-explanation. Nokes-Malach et al. (2013) compared self-explanation and analogical comparison of worked examples against worked examples with instructional explanations and found that analogical comparison led to less robust near-transfer performance than self-explanation or instructional explanations. Participants performed equally well on intermediate-transfer measures, and self-explanation and analogical comparison prompts led to greater far transfer than instructional explanations.

The present study aimed to compare the types of transfer supported by self-explanation and analogical comparison prompts, while exploring questionnaires as an alternative for quantifying the degree to which learners engage in self-explanation and analogical comparison. For both techniques, learning depends on the design of the materials including the amount of scaffolding to support analogical comparison (Gentner et al., 2003) or the focus of the self-explanation prompts (Nokes et al., 2011). We aimed to control factors such as the amount of scaffolding provided (introduction to the process, modeling, and prompting) and the target of the prompts (worked examples). Controlling these factors should provide clearer evidence about types of knowledge each technique supports.

We conducted an experiment in which learners studied text about electricity and electric circuits; received worked examples illustrating relevant concepts with prompts to self-explain, engage in analogical comparison, or study instructional explanations; and solved practice problems. All participants self-reported their use of self-explanation and analogical comparison after the conclusion of the learning phase, and they completed a test with items targeting near, intermediate, and far transfer, as well as preparation for future learning (PFL) transfer, which examines how well participants were prepared to learn from a new instructional resource about a related topic (Bransford & Schwartz, 1999). Specifically, we tested the following hypotheses:

(H1) Prompts to self-explain or compare worked examples will lead to greater far and PFL transfer than prompts to study instructional explanations, as both self-explanation and analogical comparison support the generation of abstract, flexible knowledge that transfers to new situations. By minimizing surface features, analogical comparison may reduce near transfer.

(H2): Prompts to self-explain and compare will lead to greater self-reports of self-explanation and analogical comparison, respectively.

(H3) Self-reports of self-explanation and analogical comparison will predict transfer beyond the differences explained by condition assignment. Self-reported analogical comparison and self-explanation will be associated with more far and PFL transfer, while self-reported analogical comparison may also be associated with less near transfer.

Methods

The experiment had a between-subjects design with participants randomly assigned to one of three conditions: self-explanation, analogical comparison, or instructional explanation. Participants received the same questionnaires, tests, and basic learning materials. We describe differences across the conditions below.

Participants

One hundred and one students enrolled in an introductory psychology course at the University of Pittsburgh took part in the study. Participants received credits toward a research participation requirement associated with the course.

Materials

Questionnaires Drawing from theory and prior research, we identified critical features of analogical comparison and self-explanation to develop questionnaires asking students about their use of these processes. Ten items targeted self-explanation, e.g., "During the activity, as I solved a problem I would explain to myself what concepts were being applied and why," and 11 items examined analogical comparison, e.g., "During the activity, I compared the different problems to one another to improve my understanding of how to solve them." All items were framed at the task level, and participants rated how much they agreed or disagreed with each item on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Zepeda and Nokes-Malach (2015) examined the validity of these questionnaires and found that seven self-explanation items loaded onto one factor (CFI = .924, α = 0.81) and six analogical comparison items load onto one factor (CFI = .987, α = 0.89). Therefore, we examine only those items.

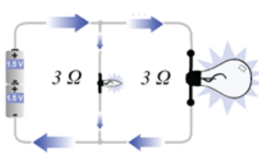
Learning materials Four booklets of instructional materials were adapted from a prior study by Richey and Nokes-Malach (2013) and covered concepts related to electricity and electric circuits. Most college students have had prior exposure to these concepts yet still hold a number of misconceptions about the topic (Slotta & Chi, 2006). The topic was well suited for examining types of transfer and included concepts and relations that could be identified through analogical comparison or self-explanation.

Each booklet contained several pages of instructional text followed by worked examples and practice problems related to the preceding text. Booklets differed across conditions in the instructions participants received while studying worked examples and solving problems. The analogical comparison condition was instructed to compare worked examples ("What is similar across problems? What is different? What do the similarities and differences tell you about the concepts involved?"); the self-explanation condition was instructed to generate explanations of worked examples ("Self-explain the reasoning or justification for this solution. Write out words to describe any symbols, and provide conceptual justifications and principled reasoning to explain the solution"); and the instructional explanations condition was instructed to study the examples ("Remember to take your time and study each worked example carefully").

Participants in the self-explanation and analogical comparison conditions studied and elaborated on a modeled response to the prompt after the first worked example in the first booklet. For example, in the self-explanation condition, participants read examples of elaboration, monitoring, and bridging statements and wrote statements of their own. Modeling self-explanation has been shown to improve the quality and effectiveness of responses (McNamara, 2004).

Worked examples were created in pairs with surface dissimilarities (e.g., different values, cover stories) and either the same or contrasting relations. Each pair of worked examples also had a corresponding practice problem with surface dissimilarities but the same relations. Worked example pairs were presented side-by-side on the same page in the analogical comparison condition. To suppress spontaneous comparison, they were presented on sequential pages in the self-explanation and instructional explanation conditions. Instructional explanations focused on concepts related to each example step and were similar to elaborative explanations participants in the self-explanation condition were expected to generate on their own (Schworm & Renkl, 2006). They were included to suppress spontaneous self-explanation in the instructional explanation condition and control the amount of information reviewed across conditions while manipulating the processes (reading, self-explaining, comparing).

Figure 1 shows a worked example from the instructional explanations condition; the self-explanation and analogical comparison conditions saw the same example with the step-by-step solution (right column) but without the instructional explanations (left column). The analogical comparison condition saw the example side-by-side with the next example, which asked the same question and included a diagram of a series circuit with two 3-ohm light bulbs. This example corresponded to several test problems, including a near-transfer question asking about current in a two-loop



5. What type of circuit is this?

Calculate the current in each branch based on the information given about the circuit, as well as the total current in the circuit.

General principle applied: Identify the type of circuit. A series circuit has one path and current is the same at every point. A parallel circuit has multiple paths and current can differ across paths.	*This is a parallel circuit. Therefore, we must calculate the current through each path of the circuit.*
Define values and relations: Voltage is the same across each branch because all the branch points are on the same wire.	*This is a parallel circuit, so voltage is the same across each branch. Voltage is 3 V in each branch.*
Define values and relations: Resistance (R) measures how difficult it is for electrons to move in a circuit, or the opposition to the movement of current (I). Resistance can differ across branches.	*Branch 1 has resistance of 3 Ω and branch 2 has resistance of 3 Ω. Use Ohm's law to calculate current in each branch and Kirchhoff's current law for total current.*
Solve based on values and principle: Set up separate equations solving for current in each branch and total current.	Branch 1 current: $I_1 = V \div R_1$ Branch 2 current: $I_2 = V \div R_2$ Total current: $I_T = I_1 + I_2$
Solve based on values and principle: To solve for current in each branch current, divide voltage by resistance. Total current is the sum of current across all branches.	$I_1 = 3\ V \div 3\ \Omega = 1\ A$ $I_1 = 3\ V \div 3\ \Omega = 1\ A$ $I_T = 1\ A + 1\ A = 2\ A$

Figure 1. Worked example with instructional explanations.

parallel circuit with new values for resistance; an intermediate-transfer question asking about resistance in a three-loop parallel circuit; and a far-transfer question asking how total current changes in a parallel circuit when additional branches are added.

Test materials A five-item pretest and 36-item posttest measured knowledge and transfer. The posttest included multiple-choice and short-answer questions, with 13 near-transfer items (α = .33), 17 intermediate-transfer items (α = .61), 12 far-transfer items (α = .44), and nine PFL transfer items (α = .53). A learning resource about power was embedded in the test and provided information for all PFL questions. Two independent coders coded all short-answer items using a rubric, discussed any differences, and reached 100 percent agreement for all items.

Procedure

Participants completed the experiment individually in sessions of three to five students at a time. After completing a brief pretest, participants worked through the self-paced learning booklets. Participants were notified of a time limit for each booklet (15 minutes for the first, 20 for the second, 25 for the third, and 30 for the fourth) and booklets were distributed one at a time. While participants could flip back or ahead within each booklet, they could not go back to a previous booklet and could not move ahead until everyone in the room had finished the current materials. Upon completing the learning booklets, participants responded to the questionnaires, as well as metacognition and task-framed achievement goal questionnaires. Participants then were given 55 minutes to complete the posttest, followed by domain-framed achievement goals and demographic questionnaires. Given space constraints, we do not discuss the metacognition, achievement goal, or demographic questionnaires further. Most sessions used the majority of the time allotted, and there were no effects of condition on learning time, $F(2, 98) = 1.40$, $p = .25$, $\eta_p^2 = .028$, or test time, $F(2, 98) = .25$, $p = .78$, $\eta_p^2 = .005$.

Results

Analyses focused on testing the effects of learning condition on each type of posttest transfer and on questionnaire responses. We also examined relations between participants' questionnaire responses and posttest performance. Posttest transfer is reported as the number of correct items out of the total number of items for each type of transfer. Post hoc comparisons were conducted using the Tukey HSD test.

H1: Condition effects on learning

We conducted a series of one-way analyses of variance (ANOVAs) to assess the effect of condition on the pretest and type of transfer the posttest (Figure 2). There was no effect of condition on pretest accuracy, $F(2, 98) = .64$, $p = .53$, $n_p^2 = .013$, so we did not control for pretest in the posttest analyses. A one-way ANOVA revealed a marginal

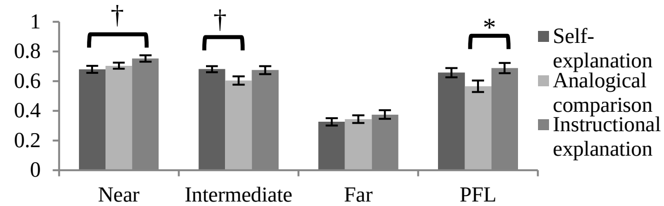


Figure 2. Learning condition effect on posttest accuracy. * indicates $p < .05$, † indicates $p < .10$.

effect of condition on near transfer, $F(2, 98) = 2.91$, $p = .059$, $\eta_p^2 = .056$. Post hoc comparisons indicated that the mean score for the instructional explanation condition ($M = .75$, $SD = .12$) was marginally different from the self-explanation condition ($M = .68$, $SD = .14$; $p = .051$). The analogical comparison condition ($M = .70$, $SD = .12$) did not differ from the instructional explanation ($p = .26$) or self-explanation conditions ($p = .70$).

There was a marginal effect of condition on intermediate transfer, $F(2, 98) = 2.89$, $p = .060$, $\eta_p^2 = .056$. Post hoc comparisons indicated that the mean score for the analogical comparison condition ($M = .60$, $SD = .16$) was marginally different from the self-explanation condition ($M = .68$, $SD = .12$; $p = .081$). The instructional explanation condition ($M = .67$, $SD = .15$) did not differ from the self-explanation ($p = .98$) or analogical comparison conditions ($p = .12$). There was no effect of condition on far transfer, $F(2, 98) = 0.83$, $p = .44$, $\eta_p^2 = .017$.

There was a medium effect of condition on PFL transfer, $F(2, 98) = 3.34$, $p = .039$, $\eta_p^2 = .064$. Post hoc comparisons indicated that the mean score for the instructional explanation condition ($M = .69$, $SD = .20$) was significantly different from the analogical comparison condition ($M = .57$, $SD = .22$: $p = .040$). However, the self-explanation condition ($M = .66$, $SD = .18$) did not differ from the instructional explanation ($p = .81$) or analogical comparison conditions ($p = .15$).

H2: Condition effects on processing

Next, we conducted ANOVAs to test the effect of condition on participants' self-reported use of self-explanation and analogical comparison (Figure 3). There was no effect of condition on self-reported self-explanation, $F(2, 98) = .77$, $p = .47$, $n_p^2 = .015$, or on self-reported analogical comparison, $F(2, 98) = 0.35$, $p = .71$, $n_p^2 = .007$.

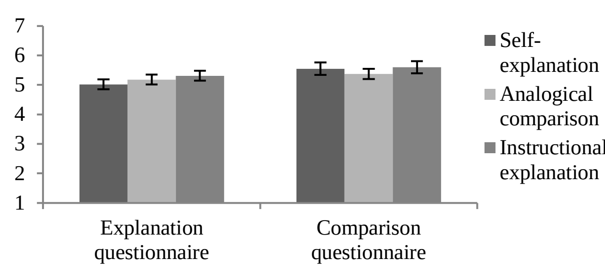


Figure 3. Results of learning condition effect on self-reported use of self-explanation and analogical comparison.

H3: Strategy use and learning

To test the amount of variance in posttest performance explained by self-reported self-explanation and analogical comparison, variance due to the condition assignment was removed using hierarchical multiple regression. Condition was dummy-coded with the worked examples-only condition as the reference group. Self-reported levels of self-explanation and analogical comparison were entered in a step-wise fashion into the second model with the first model containing the condition assignment variables.

The model predicting near transfer explained 14.7% of the variance as indexed by the adjusted R^2 statistic, $F(4, 96) = 5.32$, $p = .001$. Within the model, there was an effect of self-reported analogical comparison, $\beta = -.38$, $t = 3.39$, $p = .001$, and of self-reported self-explanation, $\beta = .38$, $t = 3.40$, $p = .001$, independent of condition assignment. Controlling for self-reported processing, there was an effect of self-explanation condition, $\beta = -.22$, $t = 2.06$, $p = .043$, and a marginal effect of analogical comparison condition, $\beta = -.19$, $t = 1.77$, $p = .080$. The model predicting intermediate transfer explained 12.3% of the variance as indexed by the adjusted R^2 statistic, $F(4, 96) = 4.51$, $p = .002$. Within the model, there was an effect of self-reported analogical comparison, $\beta = -.23$, $t = 2.05$, $p = .044$, and of self-reported self-explanation, $\beta = .39$, $t = 3.41$, $p = .001$, independent of condition assignment. Controlling for self-reported processing, there was an effect of analogical-comparison condition, $\beta = -.22$, t = 2.03, $p = .045$, and no effect of self-explanation condition, $\beta = .072$, t = 0.66, $p = .51$. The model predicting far transfer explained 2.8% of the variance as indexed by the adjusted R^2 statistic, $F(4, 96) = 1.71$, $p = .15$. The model predicting PFL transfer explained 7.0% of the variance as indexed by the adjusted R^2 statistic, $F(4, 96) = 2.88$, $p = .027$. Within the model, there was an effect of self-reported analogical comparison, $\beta = -.25$, $t = 2.13$, $p = .036$, and no effect of self-reported self-explanation, $\beta = .18$, $t = 1.52$, $p = .13$, independent of condition assignment. Controlling for self-reported processing, there was an effect of analogical-comparison condition, $\beta = -.29$, $t = 2.60$, $p = .011$, and no effect of self-explanation condition, $\beta = -.048$, $t = 0.43$, $p = .67$.

Discussion

In summary, instructing participants to study worked examples with instructional explanations led to greater PFL transfer compared to instructions to compare worked examples. There was no relation between learning condition and self-reported levels of self-explanation and analogical comparison. However, participants' self-reports of analogical comparison were significant, negative predictors of near, intermediate, and PFL transfer on the posttest. Self-reports of self-explanation were significant, positive predictors of near and intermediate transfer and a marginal, positive predictor of PFL transfer. Finally, when controlling for participants' self-reported behaviors, condition effects emerged such that self-explanation predicted marginally less near transfer compared to instructional explanations, and analogical comparison predicted marginally less intermediate transfer and significantly less PFL transfer compared to the instructional explanation condition.

These results raise several important questions. First, why was there no relationship between instructional condition and self-reported levels of self-explanation and analogical comparison? Prior work has shown that self-explanation and analogical comparison are effortful and subject to much individual variation, even when explicit instructions are given to engage in these processes (e.g., Chi et al., 1994; Gick & Holyoak, 1983). It is possible that individuals' spontaneous strategy-use tendencies and study preferences guided their learning processes more than condition assignment. This is supported by evidence showing that self-reported use of analogical comparison and self-explanation predicted performance, suggesting these measures were meaningful. However, the lack of any relationship between condition assignment and self-reported explanation and comparison behaviors suggests either a problem with the manipulation (e.g., that the prompts and modeled responses were not specific enough to guide participants' behaviors as intended) or the questionnaire (e.g., some items may have been misaligned to the task). Many students have poor awareness of their own cognitive strategy use and may have struggled to report what they actually did during the learning phase (Metcalfe, Eich, & Castel, 2010). Prior research also shows that not all self-explanations or analogical comparisons lead to robust knowledge. The questionnaire focused on *frequency* but not *quality* of self-explanations or analogical comparisons. Analysis of participants' responses to the prompts in the learning booklets could clarify these possible explanations.

Second, why did analogical comparison lead to worse performance, regardless of whether it was assigned (through condition) or spontaneous (as reflected in self-reported levels)? Some prior work has reported similar results on certain types of tasks. Nokes-Malach et al. (2013) found that analogical comparison of physics problems led to worse near-transfer performance compared to self-explanation and studying instructional explanations, although the disadvantage did not persist on intermediate- or far-transfer items. Edwards (2014) found that instructions to compare exemplars in a group were less effective for category learning than instructions to explain because the comparison prompts constrained the types of comparison learners made. More broadly, prior work has shown that adding scaffolding that identifies key features leads to greater learning from analogical comparison, as learners may struggle to align structural features without guidance (Gentner et al., 2003). Thus, one possible explanation for the negative relationship between analogical comparison and performance could be that neither the experimental manipulation to support analogical comparison nor the learners' spontaneous comparisons consistently targeted structural relations.

Edwards (2014) also found that participants instructed to engage in explanation reported greater levels of explanation *and* comparison when asked to rate their behaviors on a single-item scale. Although these results differ from our findings that neither condition reported greater levels of explanation or comparison, they are similar in showing that participants' self-reported behaviors differed from the processes the experimental manipulations were intended to support. These results suggest that instructions to compare or explain likely alter learners' behaviors in a broader range of ways and encourage changes (or perceived changes) in multiple cognitive processes. Materials were designed to suppress spontaneous comparison or explanation outside the targeted conditions, but it is possible students still engaged in analogical comparison across pages or elaborated on worked examples. Self-explanation and analogical comparison prompts may have led to more variation in what learners did while studying the worked examples. If learners in the instructional explanation condition more consistently attended to the information in the examples, they might have better learned the basic content.

Future work should continue to investigate how analogical comparison and self-explanation operate and interact to promote transfer. Questionnaires capturing specific sub-processes of analogical comparison and self-explanation might improve understanding of how each facilitates learning. By improving understanding of differences between analogical comparison and self-explanation, we hope to learn when and how instructors can support each process based on their instructional goals.

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