The Effects of Learning Multiple Instantiations on Transfer

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Abstract

The effects on transfer of learning multiple instantiations were investigated. Undergraduate college students learned one or more artificial instantiations of a simple mathematical concept. Some students were presented with instantiations that communicated concreteness relevant to the to-be-learned concept, while others learned generic instantiations involving abstract symbols. Learning one or more concrete instantiations resulted in little or no transfer. While learning one concrete and one generic instantiation did result in transfer, it offered no benefit over learning only one generic instantiation. These findings suggest that learning a generic instantiation may be a direct route to an abstract schematic representation that promotes transfer.

Keywords: Cognitive Science; Psychology; Education; Learning; Transfer; Analogical reasoning, Schema.

Introduction

Considerable research has been conducted to investigate analogical transfer. This research has produced a consensus on several important aspects of transfer. First, spontaneous transfer is often difficult to achieve (Gick & Holyoak, 1980, 1983; Reed, Ernst, & Banerji 1974; Ross, 1987, 1989). Second, superficial similarities between the learned and novel domains can influence transfer (Holyoak & Koh, 1987; Holyoak & Thagard, 1997; Ross, 1989) with near transfer to superficially similar instances more likely to occur than far transfer to superficially dissimilar instances. Third, successful transfer involves alignment of common structure across learned and novel domains (Gentner, 1983, Gentner & Markman, 1997; Holyoak & Thargard, 1989).

Our previous research has investigated another aspect of transfer, the nature of the learning domain, which has received less attention than inter-domain similarity and structural alignment. We argue that successful transfer is also a function of the concreteness of the learning domain. We interpret concreteness to be extraneous information present in a given conceptual instantiation. This information might be perceptual or conceptual (i.e. tapping prior knowledge). Analogical transfer is more likely to occur after learning an abstract, generic instantiation than after learning a concrete (contextualized or perceptually rich) instantiation (Kaminski, Sloutsky, & Heckler, 2005, 2006; Sloutsky, Kaminski, & Heckler, 2005; see also Bassok & Holyoak, 1989; Goldstone & Sakamoto, 2003 for related findings). In particular, we found that concreteness that benefited quick learning resulted in difficulty with recognition and alignment of common structure across domains and consequently transfer failure (Kaminski, Sloutsky, & Heckler, 2006). At the same time, learning a generic instantiation resulted in successful structural alignment and transfer.

Although concrete instantiations resulted in poor transfer compared to generic instantiations, some may argue, on practical grounds, for the use of such instantiations in teaching abstract concepts such as mathematical and scientific concepts. These concepts are often difficult for students to grasp. Concrete instantiations may be more likely than generic, symbolic instantiations to engage students in the process of learning. Furthermore, given that some concrete instantiations can facilitate initial learning, perhaps learning experiences can be designed which use such concrete instantiations while overcoming obstacles to transfer.

One possible way of overcoming negative effects of concreteness is to use multiple concrete instantiations. It has been suggested that when a learner encounters multiple examples of a concept, a schematic representation is formed that will lead to successful future transfer (Gick & Holyoak, 1983; Novick & Holyoak, 1991; see also Reed, 1993 for discussion). For example, Gick and Holyoak (1983) investigated the effect on transfer of problem solving strategies from learning one or two instantiations. They found that 45% of study participants who learned two analogues successfully transferred, while only 21% transferred when given only one instantiation. With a suggestion that previous knowledge would be useful in the novel situation, 80% of participants transferred from two analogues while 53% transferred from one instantiation.

While there is evidence that learning multiple instantiations may result in successful transfer perhaps via schema formation, there are also reasons to believe that schema formation and transfer may not be guaranteed, especially when multiple instantiations are concrete. First, transfer and most likely schema formation require recognition and alignment of common structure (Gentner, 1983, Gentner & Markman, 1997; Holyoak & Thargard, 1989); and relational structure common to two situations is less likely to be noticed when the situations are represented in a more concrete, perceptually rich manner than in a more generic form (Gentner & Medina, 1998; Markman & Gentner, 1993). Second, we have found in a previous experiment that participants who learned a concrete instantiation were unable to recognize the learned structural rules when presented with novel elements suggesting that their knowledge of structure was encapsulated in the concrete learning context (Kaminski, Sloutsky, & Heckler, 2006). If concrete knowledge is indeed encapsulated, then there is little reason to believe that learning multiple concrete instantiations will have a substantial advantage for transfer over learning only one.

The purpose of the present research was to investigate the effects of learning multiple instantiations on subsequent analogical transfer. Undergraduate college students learned one or more instantiations of the simple mathematical concept used in our earlier studies. Then they were presented with a novel isomorphic transfer domain and asked to answer questions about it.

Experiment 1

Method

Participants Eighty undergraduate students from Ohio State University participated in the experiment and received partial credit for an introductory psychology course. Students were randomly assigned to one of four conditions that specified the type and number of instantiations they learned.

Materials and Design The experiment consisted of two phases. In phase 1, participants learned one, two, or three instantiations of a mathematical concept. The instantiations were either generic or concrete. There were four between-subject conditions, which specified the number and type of instantiations learned in phase 1: One Generic, One Concrete, Two Concrete, or Three Concrete. Total training was equated across condition. In phase 2, participants were tested on an isomorphic transfer domain.

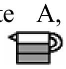
The to-be learned concept was the same concept used in our previous research (Kaminski, Sloutsky, & Heckler, 2005, 2006; Sloutsky, Kaminski, & Heckler, 2005). This was a commutative mathematical group of order three. In other words the rules were isomorphic to addition modulo three. The idea of modular arithmetic is that only a finite number of elements (or equivalent classes) are used. Addition modulo 3 considers only the numbers 0, 1, and 2. Zero is the identity element of the group and is added as in regular addition: $0 + 0 = 0$, $0 + 1 = 1$, and $0 + 2 = 2$. Furthermore, $1 + 1 = 2$. However, a sum greater than or equal to 3 is never obtained. Instead, one would cycle back to 0. So, $1 + 2 = 0$, $2 + 2 = 1$, etc. To understand such a system with arbitrary symbols (not integers as above) would involve learning the rules presented in Table 1. However, concrete contexts can be created in which prior knowledge and familiarity may assist learning. We constructed four instantiations of a mathematical group: three concrete (Concrete A, Concrete B, and Concrete C) and one generic (Generic).

The Concrete A instantiation was used in our prior research and was shown to facilitate quick learning of the rules of the mathematical group (Kaminski, Sloutsky, & Heckler, 2005). The symbols of this instantiation were three images of measuring cups containing varying levels of liquid (see Table 1). Participants were told they need to determine a remaining amount when different measuring cups of liquid are combined. In particular, and will fill a container. So for example, combining and would have remaining. Additionally, participants were told that they should always report a remainder. Therefore they should report that the combination of and would have remainder . In this domain, behaves like 0 under addition (the group identity element). acts like 1; and acts like 2. For example, the combination of and does not fill a container and so remains. This is analogous to $1 + 1 = 2$ under addition modulo 3. The perceptual information communicated by the symbols themselves can act as reminders of the structural rules. In this case, the storyline and symbols facilitate learning.

Concrete B and Concrete C instantiations were constructed similarly with storylines and symbols that would assist learning. The task for the Concrete B instantiation was to determine the amount of burned pizza served from a restaurant where the cook systematically burned a portion of every order. Three possible individual orders could be placed: 1, 2, or 3 slices, represented as , , and . The proportion that would be burned followed the rules of the mathematical group. For example, when an order for and was placed, then would be burned. For the Concrete C instantiation, participants were told of a tennis ball manufacturing machine. Instead of producing batches of 3 balls to fill each ball container, the machine was producing batches of 0, 1, or 2 balls, represented as , , and . Under these circumstances, more than one batch of balls would be combined to fill containers. Participants' task was to determine the extra balls resulting from combining batches. For example, if these two batches were combined, and , then would be extra.

The Generic instantiation was presented as a symbolic language in which three types of symbols combine to yield a resulting symbol (see Table 1). Combinations were expressed as written statements.

In the One Concrete condition, participants learned the Concrete A instantiation. In the Two Concrete condition, participants learned Concrete A and Concrete B instantiations. In the Three Concrete Condition, they learned Concrete A, B, and C instantiations. Participants in the One Generic condition learned the Generic instantiation. Training was equated across condition, so that the same examples, questions with feedback, summaries of rules, and test questions were spread across the learning instantiations.

For each instantiation, training consisted of an introduction and explicit presentation of the rules through examples. For instance, for Concrete A, participants were told that combining  and  has a remainder of . Analogously, for the Generic instantiation where students were told that symbols combine to yield a resulting symbol the analogue to the above rule was presented as ♦, ♦ → ●. Questions with feedback were given; and complex examples were shown. To approximate the effect of presenting the rules in more than one domain, additional summaries of the rules were given when learning fewer domains.

After training of an instantiation, the participants were given a multiple choice test designed to measure the ability to apply the learned rules to novel problems. In total, 24 multiple-choice questions were posed in phase 1 (learning phase). Questions were distributed evenly over the learning domains. Participants who learned two instantiations had a 12-question test over the first domain and the remaining twelve questions over the second domain. Participants who learned three instantiations had 8-question tests over each domain. Participants who learned only one instantiation were given a 24-question test. Many questions required application of multiple rules. The following are examples of test questions for the Generic instantiation.

(1) What can go in the blanks to make a correct statement?

___, ♦, ___, ● → ●

(2) Find the resulting symbol:

♦, ●, , ♦ → ____

The concrete instantiations presented the analogues of these questions.

After training and testing of the learning domains, a novel transfer domain was presented. The same transfer domain was used for all four conditions and was described as a children's game involving three objects (see Table 2). Children sequentially point to objects and a child who is "the winner" points to a final object. The correct final object is specified by the rules of the game (rules of a mathematical group). Participants received no explicit training in the target domain. They were not explicitly taught the rules of the system. Instead they were told that the game rules were like the rules of the system(s) they just learned and they need to figure them out by using their newly acquired knowledge (i.e transfer). After being asked to study a series of examples. from which the rules could be deduced, a 24-question multiple-choice test was given. The questions on this test were isomorphic to those given in phase 1. Questions were presented individually on the computer screen along with four key examples at the bottom of the screen. The same four

Table 1: Stimuli and rules across Concrete A and Generic instantiations.

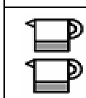
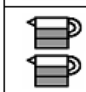
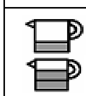
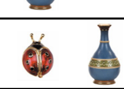
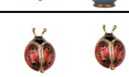
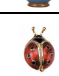
	Concrete A		Generic	
Elements			● ♦ 	
Rules of Commutative Group:				
Associative	For any elements x, y, z: $((x + y) + z) = (x + (y + z))$			
Commutative	For any elements x, y: $x + y = y + x$			
Identity	There is an element, **I**, such that for any element, x: $x + \mathbf{I} = x$			
Inverses	For any element, x, there exists another element, y, such that $x + y = \mathbf{I}$			
Specific Rules:	 is the identity		 is the identity	
	Operands	Remainder (Result)	Operands	Result
			● ●	♦
			♦ ♦	●
			● ♦	

Table 2: Stimuli for transfer domain.

Elements:		
Examples:	If the children point to these objects:	The winner points to this object
		
		
		
		

examples were shown with all test questions. Following the multiple-choice questions, participants were asked to match each element of the transfer domain to its analogous element in the first or only learning domain.

In previous experiments (Kaminski, Sloutsky, & Heckler, 2005), no participant was able to score above chance on a test of the transfer domain without first learning an isomorphic domain. Therefore, in the present experiment, transfer test scores that are above chance suggest successful transfer of conceptual knowledge. Also, note that in a separate experiment, adults who read descriptions of the learning and transfer domains, but received no explicit training of the rules, found both the generic and concrete domains equally similar to the target domain. Thus, any differences in transfer performance across conditions cannot be attributed to differential similarity of learning and transfer domains.

Procedure Training and testing were presented to individual participants on a computer screen in a quiet room. They proceeded through training and testing at their own pace; and their responses were recorded.

Results and Discussion

Eight participants (Three Two Concrete, three Three Concrete, and two One Generic) were eliminated from the analysis for failing to learn as evidenced by learning score(s) not above chance. Chance score for total learning was 9 out of 24, or 37.5%. The criterion for learning was composite learning score (the sum of scores in all learning domains) as well as learning scores in each individual instantiation above chance.

In all conditions, participants successfully learned the material (see Table 3). Composite learning scores were significantly above chance, one-sample t-tests, *t*s > 9.62, *p*s < .001; and there were no differences across condition, one-way ANOVA, $F\,(3, 68) = .697$, $p > .55$. In addition, learning in each individual learning domain was above chance, one-sample t-tests, *t*s > 8.84, *p*s < .001.

Most importantly, transfer performance differed across conditions (see Figure 1). Transfer scores were submitted to a one-way ANOVA. Results revealed a significant effect of learning condition, $F\,(3, 68) = 11.93$, $p < .001$, $\eta_p^2 = .345$,

Table 3: Learning scores (% correct) by instantiation.

	1st Instant.	2nd Instant.	3rd Instant.	Composite Learning Score
Condition	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*
One Concrete	75.8 (17.8)	-	-	75.8 (17.8))
Two Concrete	82.3 (15.6)	74.5 (19.2)	-	78.4 (16.5)
Three Concrete	80.1 (16.0)	78.6 (13.8)	89.0 (12.4)	82.6 (8.75)
One Generic	80.3 (13.7)	-	-	80.3 (13.7)

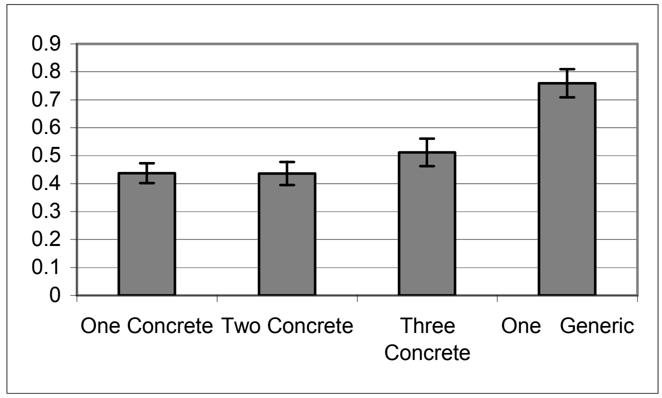


Figure 1: Mean Transfer Test Scores (% Correct).
Note: Error bars represent standard error of mean.
Chance score is 37.5%.

participants in the One Generic condition performed markedly higher than participants in each of the other three concrete conditions, post-hoc Tukeys, *p*s < .002. At the same time there were no differences in transfer scores across the three concrete conditions, post-hoc Tukeys, *p*s > .626. Transfer in the Generic condition was clearly above chance, one-sample t-test, $t(17) = 7.55$, $p < .001$, while transfer in the One and Two Concrete conditions was not, *t*s < 1.7, *p*s > .09. Transfer in the Three Concrete condition was only marginally above chance, $t(16) = 2.78$, $p = .013$.

In addition to differential transfer, the ability to match analogous elements between the first or only learning instantiation and the transfer instantiation was also significantly different. Eighty-three percent of participants in the One Generic condition correctly matched elements, while only 30%, 24%, and 41% of participants made the correct matches in the One Concrete, Two Concrete, and Three Concrete conditions respectively. Note that the expected proportion due to random guessing would be 33%.

These findings indicate that learning two or three concrete instantiations offered no advantage for transfer over learning only one concrete instantiation. Participants in the concrete conditions were generally unable to match analogous elements across learning and transfer domains which suggests that they were unable to align common structure. These results contradict schema theories that propose that learning multiple instantiations will lead the learner to form an abstract schematic representation of the relevant concept that will in turn promote analogical transfer.

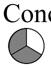
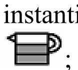
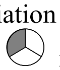
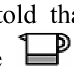
However, it could be argued that transfer was poor when learning multiple instantiations because participants did not align the learning instantiations. Abstraction of structure may not be automatic, instead it may result from the deliberate structural alignment, for example in the course of comparison (Kotovsky & Gentner, 1996; Ross & Kennedy, 1990). We also have evidence that alignment between a learning and a transfer domain does promote transfer (Kaminski, Sloutsky, & Heckler, 2006). Therefore, it is possible that assisting the learners with structural alignment between two learning domains may also result in successful transfer. The purpose of Experiment 2 was to examine this possibility.

Experiment 2

Method

Participants Twenty undergraduate students from Ohio State University participated in the experiment and received partial credit for an introductory psychology course.

Materials, Design and Procedure The materials and procedure of this experiment were almost identical to that of Experiment 1, with two differences. First, all participants learned two concrete instantiations, Concrete A and Concrete B. Second, participants were given the correspondence of analogous elements between the two learning instantiations.

Therefore, participants were trained on Concrete A instantiation and were given a 12-question multiple-choice test. Then participants were trained on Concrete B instantiation and told that  is like ;  is like ;  is like . Participants were given a 12-question multiple-choice test on Concrete B instantiation. As in Experiment 1, participants were presented with the novel transfer domain, shown examples, and given a 24-question multiple-choice test analogous to the questions posed over the two concrete learning instantiations.

Results and Discussion

All participants successfully learned. Scores in each of the learning domains were above chance (M = 88.3%, SD = 9.58 and M = 76.7%, SD = 16.2, respectively), one sample t-test, t(19)s > 12.0, ps < .001. However, transfer scores were not above chance (M = 41.2%, SD = 16.7), one sample t-test t (19) = .943, p > .356 (see Figure 2).

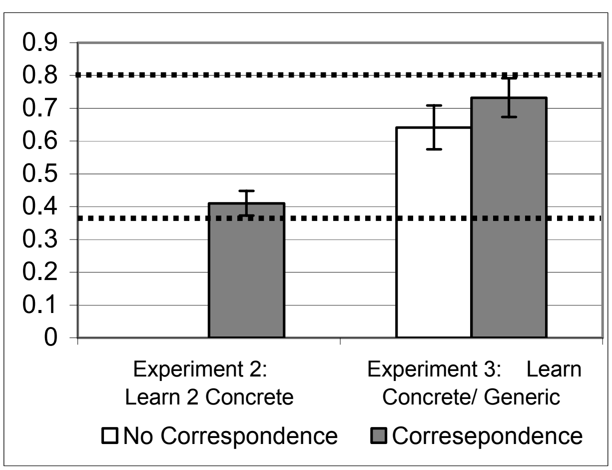


Figure 2: Mean Transfer Test Scores (% Correct).
Note: Error bars represent standard error of mean.
Lower dashed horizontal line represents chance score. Upper dashed horizontal line represents mean Generic transfer score.

Along with failing to transfer, participants were unable to correctly match analogous elements between the first learning instantiation and the transfer instantiation. Only 15% made the correct correspondence. Apparently assisting participants in structural alignment between two concrete learning instantiations did not lead to the formation of an abstract schema that can promote transfer. While transfer failed when learning one or more concrete instantiations, learning one generic instantiation did allow for successful structural alignment and transfer (see Experiment 1). Another possible learning design is to first learn a concrete instantiation that might facilitate learning and then learn a generic instantiation which has been shown to allow transfer. The goal of Experiment 3 was to consider whether learning one concrete and then one generic instantiation would offer an advantage for transfer over learning only one generic.

Experiment 3

Method

Participants Forty undergraduate students from Ohio State University participated in the experiment and received partial credit for an introductory psychology course.

Materials, Design and Procedure The materials, design, and procedure were similar to those of the previous experiments. Participants learned two instantiations of the mathematical group, first Concrete A and then Generic. There were two between-subject conditions: Correspondence and No Correspondence. In the Correspondence condition, participants were given the correspondence of analogous elements between the Concrete A and Generic instantiations (as in Experiment 2). In the No Correspondence condition, they were not. As in the previous experiments, there were 12-question multiple-choice tests in each of the two learning domains and a 24-question multiple-choice test in the transfer domain.

Results and Discussion

Eight participants (three Correspondence, five No Correspondence) were removed from the analysis for failing to learn (i.e. composite learning scores and scores in each learning domain were not above chance).

Participants successfully learned the concrete (M = 88.3%, SD = 6.14, M = 84.2%, SD = 12.5, for No Correspondence and Correspondence respectively) and generic instantiations (M = 77.5%, SD = 19.5, M = 72.5%, SD = 18.3, for No Correspondence and Correspondence respectively).

Unlike in Experiment 2, transfer scores were well above chance, one-sample t-tests, ts > 4.0, ps < .002 (see Figure 2) with no significant differences between the Correspondence and No Correspondence groups, independent sample t-test, t(30) = 1.02, p > .311. To consider whether learning both a concrete and a generic instantiation benefits transfer more than learning only a generic instantiation, transfer scores were compared to a mean transfer score of participants who learned the generic instantiation. This mean (80%) was calculated from the results of Experiment 1 and three prior studies (see Kaminski, Sloutsky, & Heckler, 2005; Kaminski, Sloutsky, & Heckler, 2006). Transfer was marginally higher for one generic than concrete-then-generic without assisting alignment, one sample t-test $t(14) = 2.31$, $p = .036$, and no higher than learning concrete-then-generic with assisting alignment, one sample t-test $t(16) = 1.06$, $p = .302$.

Participants were generally able to make the correct match of analogous elements, 87% in the No Correspondence condition and 71% in the Correspondence condition. This is particularly interesting because participants were able to match the novel transfer domain elements with the concrete elements first learned, after having learned the generic instantiation. In comparison, participants in Experiment 1 who learned only the concrete instantiation were unable to correctly match these elements.

General Discussion

The results of this study make several important points. First, learning multiple instantiations does not necessarily lead to successful transfer. Learning two or three concrete instantiations resulted in little or no transfer and no improvement over learning only one concrete instantiation. How does this finding reconcile with the effectiveness of multiple instantiations found by other researchers (e.g. Gick & Holyoak, 1983)? One possible explanation is differential complexity of the to-be-learned concept. The mathematical concept involved in the present research is perhaps more complex than concepts/ solution strategies used in other work. Second, learning a concrete and then a generic instantiation did allow for successful transfer, but offered no advantage over simply learning one generic. Third, structural alignment and abstraction is spontaneous when learning involved a generic instantiation. At the same time, concrete knowledge appears to be encapsulated, making structural alignment and schema formation difficult. Taken together, these findings suggest that learning a generic instantiation can be an efficient route to forming a schematic representation that can facilitate transfer.

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