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Mechanisms of knowledge transfer

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A central goal of cognitive science is to develop a general theory of transfer to explain how people use and apply their prior knowledge to solve new problems. Previous work has identified multiple mechanisms of transfer including (but not limited to) analogy, knowledge compilation, and constraint violation. The central hypothesis investigated in the current work is that the particular profile of transfer processes activated for a given situation depends on both (a) the type of knowledge to be transferred and how it is represented, and (b) the processing demands of the transfer task. This hypothesis was investigated in two laboratory training studies. The results from Experiment 1 show that each mechanism predicts specific behavioural patterns of performance across a common set of transfer tasks. The results from Experiment 2 show that people can adaptively shift between transfer mechanisms depending on their prior knowledge and the characteristics of the task environment. A framework for the development of a general theory of transfer based on multiple mechanisms is proposed and implications of the theory are discussed for measuring and understanding knowledge transfer.

Keywords: Knowledge representation; Learning; Problem solving; Theory unification; Transfer.

In order to understand human thinking and problem solving in complex and novel situations we need to have a general theory for how people use and adapt their prior knowledge to solve new problems. Aspirations towards such a goal have traditionally been discussed in terms of *transfer*, or how knowledge acquired from one task or situation can be applied to a different one (Barnett & Ceci, 2002; Bransford & Schwartz, 1999; Cormier & Hagman, 1987; Detterman & Sternberg, 1993; Elis, 1965; Lobato, 2006; Reeves & Weissberg, 1994; Royer, 1979; Salomon & Perkins, 1989; Singley & Anderson, 1989).

Work in cognitive science over the past 30 years has taken a "divide and conquer" approach to attaining this goal. Researchers have pursued separate lines of inquiry by investigating the cognitive processes of transfer for particular learning and problem-solving scenarios. This work has led to the development of several specialised theories of transfer including analogical transfer (Gentner, 1983; Gick & Holyoak, 1983), knowledge compilation (Anderson, 1983), constraint violation (Ohlsson, 1996), and transfer-appropriate processing (Morris, Bransford, & Franks, 1977), among others.

Although this research strategy has contributed to our understanding of particular kinds of transfer, it has done little to address how these different transfer processes relate to and interact with one another. A complementary research approach is *theory unification*. If our ultimate goal is to develop a general theory of transfer we need to articulate how each local theory "fits together" within a larger cognitive framework (Newell, 1990). The present work investigates the possibility that there are *multiple mechanisms for transfer*, each of which has psychological reality. If people have multiple transfer mechanisms then it is likely that they apply or engage those mechanisms adaptively, in response to the transfer conditions, i.e., what relevant knowledge they possess, how it is encoded, and the relation between the training and transfer problems.

In two experiments, I investigate the application conditions and interaction of three proposed mechanisms of transfer including analogy, knowledge compilation, and constraint violation. Understanding when these mechanisms are applied and how they interact is critical for developing a general theory that incorporates each mechanism in principled ways. The central hypothesis is that the particular profile of transfer processes triggered for a given situation depends on (a) the type of knowledge to be transferred and how it is represented, and (b) the processing demands of the transfer task. It is hypothesised that there is a trade-off between the mechanisms in terms of their scope of application (i.e., near vs far transfer) and the amount of cognitive processing required to transfer the knowledge. In the next section, I summarise the prior work on each of these mechanisms.

PAST WORK AND PROPOSED MECHANISMS

The first mechanism of interest is *analogical transfer* (Gentner, 1983; Gentner, Holyoak, & Kokinov, 2001; Gick & Holyoak, 1980, 1983). Analogical transfer is composed of three components: retrieving a prior exemplar, creating a mapping between it and the current problem or situation, and then using that mapping to draw an inference relevant to the application context. The transferred knowledge is typically assumed to be a declarative representation, but it can also include procedural attachments (Anderson & Thompson, 1989; Carbonell, 1986; Chen, 2002). For example, during a game of chess a player could recall a similar game board from memory based on the surface characteristics of the current board (e.g., two knights near an opponent's bishop), make an alignment and mapping of the pieces and positions from the past game to the current, and then draw an inference for what move to make in the current situation.

A target and source analogue can be similar to one another in a number of ways. They can have similarities on the surface (matching object features and context), structurally (matching relations[1] between objects), or both (matching objects and relations, *literal similarity*). A large amount of empirical work has shown that analogical retrieval is facilitated by the surface similarity to the target scenario (Catrambone, 2002; Holyoak & Koh, 1987; Novick, 1988; Ross, 1984, 1987; Ross & Kilbane, 1997) whereas alignment and mapping is facilitated by the structural similarity (Catrambone & Holyoak, 1989; Gentner & Gentner, 1983; Gentner, Ratterman, & Forbus, 1993; Gentner & Toupin, 1986; Gick & Holyoak, 1983; Keane, 1987; Novick, 1988). These results suggest that for novices[2] analogy is triggered by near transfer tasks that are similar on the surface and that share the same relational structure.

The second mechanism of interest is *knowledge compilation* proposed by John Anderson and co-workers (Anderson, 1982, 1983, 1987; Neves & Anderson, 1981). This mechanism acts as a translation device that interprets prior declarative knowledge (e.g., advice, instructions, or tactics) into a set of procedures that can be used to solve new problems. Knowledge compilation operates through the step-by-step interpretation of a declarative statement that generates new production rules as a side effect. Those production rules are then optimised via rule composition (production compilation; Taatgen & Anderson, 2002; see also Anderson et al., 2004),

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[1]Relations can vary from single, lower-order relations to higher-order relational structures and whether they are based on similarity between the relational concepts (semantics) or pure structure (graph) matches (Gentner & Kurtz, 2006; Gentner & Markman, 2006).

[2]Research on experts has shown that they are less reliant on the surface features and more likely to use the deep structures to make analogies (Novick, 1988).

and the result is a procedural representation of the content of the declarative knowledge given a particular goal. For example, after reading a text on tactics for playing chess one can then apply those tactics to a wide variety of game scenarios, even if one has never encountered those particular game situations before. Knowledge compilation is the process of figuring out the action implications of the tactics for the particular situation or problem encountered.

Since knowledge compilation operates on declarative knowledge representations, it can be brought to bear in a wide variety of application contexts because the knowledge has yet to be proceduralised or tied to the goals of a particular problem-solving context. This mechanism embodies a trade-off between applicability and efficiency in that it has wide applicability across many contexts but requires a complicated and lengthy application process to translate the declarative knowledge into a set of actions (Anderson, 1987). Previous work has shown that declarative knowledge can apply to a variety of different surface features but is costly in terms of the time required to proceduralise that knowledge to the current problem context (e.g., Nokes & Ohlsson, 2005).

The third mechanism of interest is *constraint violation* proposed by Stellan Ohlsson and co-workers (Ohlsson, 1996; Ohlsson, Ernst, & Rees, 1992; Ohlsson & Rees, 1991). This mechanism is also a declarative-to-procedural type of transfer but implements a different set of cognitive processes from those used in knowledge compilation. Constraint violation is a three-part process that involves a generate-evaluate-revise transfer cycle in which a learner uses prior knowledge of the domain constraints to evaluate and correct her or his task performance.

According to the theory, the learner generates an initial solution based on general problem-solving strategies and then evaluates that solution with respect to her or his prior knowledge of the domain constraints. If a constraint is violated, the learner attempts to revise the faulty procedure(s) and generate a new solution. This process is repeated until a correct solution is found that satisfies all of the constraints. Transfer is the process by which the learner uses her or his prior constraint knowledge to identify and remedy the errors generated while performing new tasks. For example, knowledge of the constraints in chess (i.e., avoid checkmate, bishops move diagonally, etc.) could be used to generate specific procedures for what move to make in a given situation. One would begin by generating a possible move and then would evaluate that move with regards to the domain constraints. If a constraint was violated (e.g., the king is left vulnerable for checkmate), the faulty procedure would be revised and a new procedure would be generated and evaluated. If this situation were repeated across multiple episodes, eventually the individual would acquire specific procedures for what move to make in a given situation. The theory postulates that constraint

knowledge applies to a wide variety of tasks but is costly in the amount of cognitive processing that it requires to iterate through the generate-evaluate-revise transfer cycle to obtain a correct solution.

Each of these mechanisms has been hypothesised to use different cognitive processes and has been associated with a particular type of transfer scenario (i.e., type of prior knowledge and application context). Analogy transfers prior exemplar knowledge and is applied by novices to near transfer problems that look similar on the surface. This kind of transfer is beneficial when the source has the same deep structure as the target (if the structures differ it may lead to inappropriate analogies and problem-solving errors). If procedural knowledge from the exemplar is mapped to the target problem, the solution can be articulated with minimal cognitive processing. Knowledge compilation transfers prior declarative knowledge including facts, instructions, or tactics, and can be applied to multiple problem contexts because the knowledge has yet to be proceduralised for any one task. Although the declarative knowledge can apply across a variety of different surface features, interpreting that knowledge for a particular problem requires significant cognitive processing. Finally, constraint violation transfers prior knowledge of the domain constraints and can be applied to a wide variety of problems within the domain. Although such knowledge can be applied generally, using it to derive a specific solution requires multiple iterations of the generate-evaluate-revise transfer cycle.

Comparing these mechanisms to one another suggests a trade-off between their scope of application and the amount of cognitive effort. Analogy applies to near transfer problems and is fast and efficient; knowledge compilation applies across a variety of surface features but the knowledge must be proceduralised; and constraint violation applies to many problems in a domain but requires several iterations of the generate-evaluate-revise transfer cycle. Although much progress has been made in understanding each mechanism independently, what is missing from this work is research designed to (a) test the predictions of each mechanism within one and the same task domain and (b) assess their interaction across a set of problem-solving tasks.

LOGIC OF APPROACH

These issues were investigated in two laboratory training studies. Experiment 1 was a between-participants design in which participants were given training on one of the three types of knowledge structures (exemplars, tactics, or constraints) and then solved three transfer problems. This experiment tests the behavioural predictions of each transfer mechanism across a common set of tasks and measures (e.g., accuracy, solution type, and solution time) and provides a measure of baseline performance for how

each type of knowledge (when applied separately) is used to solve the problems. Experiment 2 was a within-participants design in which participants were trained on all three knowledge structures and then solved the same three transfer problems. "Think aloud" protocols were collected to provide a fine-grained assessment of the cognitive processes used to solve the problems. This experiment tests the interaction of the three mechanisms and whether participants dynamically shift between mechanisms based on the characteristics of the transfer tasks.

PROBLEM-SOLVING DOMAIN

The problem-solving domain used was *sequence extrapolation* (Thurstone & Thurstone, 1941). In this task participants are given a sequence of symbols containing a pattern and their task is to find the pattern and continue it. As a simple example, try and generate the next six letters of the sequence CDDEFF ———. The first step of the task is to identify the pattern of relations between the given symbols. This sequence has a three-symbol repetition where the first symbol is one forward from the last symbol of the previous iteration, the second symbol is one forward from the first, and the third repeats the second. After identifying the pattern of relations one can then use those relations to continue the pattern (the correct continuation to the above sequence is GHHIJJ).

An important feature of this task is that prior knowledge of the pattern can make these problems easier to solve. In previous work we (Nokes & Ohlsson, 2003, 2005) have shown that both declarative knowledge of the pattern and procedural knowledge of the extrapolation inferences can facilitate solving new problems that have the same pattern structure. In the current work I investigate the conditions under which three knowledge structures are used to solve novel problems, specifically comparing exemplar knowledge of the pattern to tactical knowledge for finding and extrapolating patterns to constraint knowledge for how the patterns are formed.

A second critical feature of the task is that multiple levels of abstraction can be defined in regards to the pattern. Much research has shown that the level of abstraction at which a concept is learned has a large effect on subsequent transfer (see Reeves & Weissberg, 1994, for a review). Therefore, it was critical to use a task in which the level of abstraction could be defined very precisely. Three levels of abstraction are defined for the purposes of the current work.

The *surface level* abstracts over the letters but the relations between them remain the same (e.g., the following two sequences are identical at the surface level of abstraction, ABBCDD and JKKLMM). The letter positions across problems share the same role and are connected by a set of fully specified semantic relations (e.g., *forward 1*). The *intermediate*

level abstracts over the quantitative aspect of the relation but the type of relation remains the same (e.g., stretching the pattern from forward 1 to forward 2, ABBCDD and JLLNPP are identical at the intermediate level of abstraction). The letter positions across problems again share the same role but now are only connected by a partially specified relation (e.g., *forward X*). The *deep-structural level* abstracts over the type of relation (e.g., instead of forward relations they are changed to backward relations, ABBCDD and NMMLKK are identical at the deep structural level of abstraction). The letter positions again share the same role but are connected to one another by more general relations (e.g., *next to*).

Although sequence extrapolation is a laboratory task, it has several elements in common with many real-world tasks including: types of knowledge (exemplar, tactics, and constraints), conceptual content (e.g., the pattern structure), levels of abstraction (e.g., surface, intermediate, and deep), materials to study (e.g., practice problems and expository text), complexity (e.g., problems can be made arbitrarily complex), and generativity (e.g., one has to generate a novel sequence of coordinated actions to solve a given problem).

EXPERIMENT 1: TESTING MULTIPLE MECHANISMS OF TRANSFER

The goal of Experiment 1 was to test the behavioural predictions of each mechanism across a common set of transfer problems. Participants were given training on one of three knowledge types associated with each of the transfer mechanisms (exemplars for analogy, tactics for knowledge compilation, and constraints for constraint violation) and then were tested on three transfer problems (see Figure 1 for a summary of the design and materials). Each problem was constructed with different properties to elicit quantitative (accuracy and solution time) and qualitative (solution type) performance differences from the training groups.

In addition to comparing task performance across training groups, each training group was compared to a *no-training* control group for a measure of transfer relative to baseline performance. The next section describes the behavioural predictions for each of the training groups across the three transfer problems (see Table 1 for a summary).

Predictions

Transfer problem 1.   All three training groups were expected to a show large accuracy advantage over the no-training group. Participants in the exemplar group were expected to use analogy because the problem had similar surface features and the same structural relations as the exemplars.
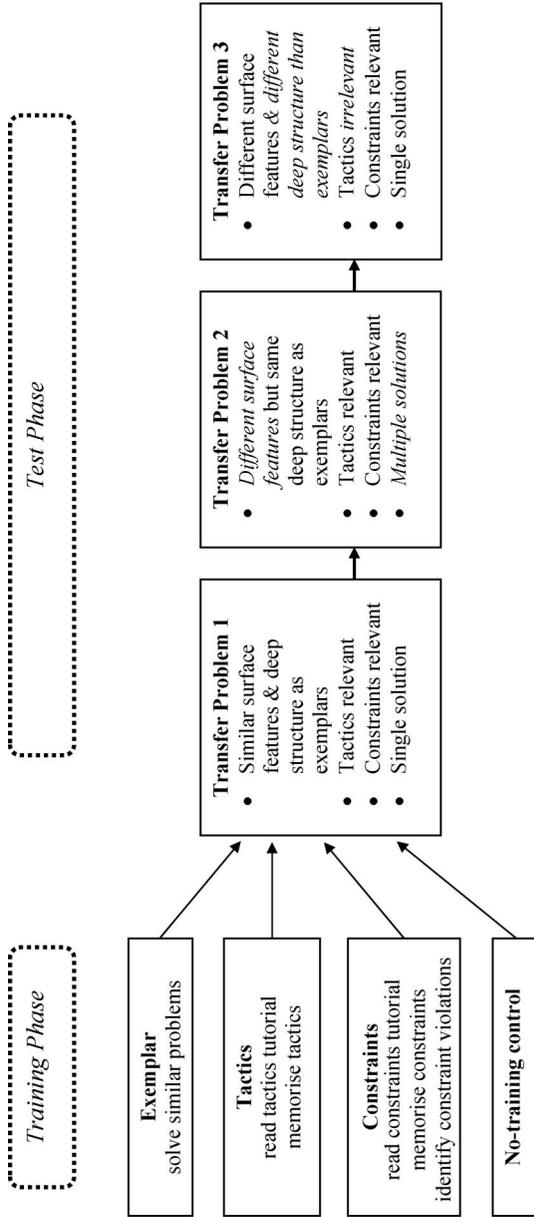
Figure 1. Summary of the design and materials for Experiment 1.

TABLE 1
Predictions for each training group relative to the no-training control group

Training	Transfer 1	Transfer 2	Transfer 3
Exemplar	**High accuracy** **Fast solution times**	Similar accuracy **Bias to surface solution** **Fast solution times**	Similar or worse Accuracy and solution times
Tactics	**High accuracy** Similar solution times	Similar accuracy **Bias to tactics solution** Similar solution times	Similar or worse Accuracy and solution times
Constraints	**High accuracy** Similar solution times	Similar accuracy No Bias Similar solution times	**High accuracy** Similar solution times

The predicted results in bold differ from those expected for the no-training group.

Participants in the tactics group were expected to use knowledge compilation because their tactical knowledge applied to the pattern, but had to be interpreted for the particular problem context. Participants in the constraints group were expected to use constraint violation because their constraint knowledge applied to the problem, but it could only be used to assess solutions, encouraging a generate-evaluate-revise solution process.

Solution times were collected as a measure of the amount of cognitive processing. The exemplar group was expected to show the fastest solution times because the surface match should facilitate the recall of the training problems and the structure match should facilitate analogical alignment and mapping. In addition, transfer of procedural knowledge should further reduce their problem-solving times because the necessary extrapolation procedures would have already been created. In contrast, participants in the tactics and constraints groups were not expected to show a solution time advantage over the no-training group because both knowledge compilation and constraint violation are hypothesised to require significant amounts of cognitive processing (i.e., interpreting each of the tactics and executing multiple iterations of the generate-evaluate-revise transfer cycle).

Transfer problem 2. All three training groups were expected to show high accuracy for this problem. However, the relative advantage over the no-training group was expected to be small since the problem was open-ended and there were multiple solutions (i.e., increasing the probability that the no-training participants could generate a correct one). Therefore, the primary measure of interest was the *solution type*. Depending on how the problem sequence was interpreted, different types of solutions were

expected. The problem had the same deep structure as the exemplar problems but changed some of the surface features and relations. If the sequence was interpreted as similar to the remaining surface features, but with a different deep structure, one solution was expected. If it was interpreted as a deep analogy, a second solution was expected.

Exemplar participants were expected to generate the *surface-similar solution*. Since these participants were expected to encode the exemplar problems at the surface level of abstraction, they would be unlikely to notice the deep structural relations. In contrast, the participants from the tactics training group were expected to show a bias for generating the second, "tactics", solution because their knowledge applied directly to this interpretation of the pattern. Finally, the constraints training participants were expected to generate solutions similar to the no-training participants because the constraints applied equally well to the five possible solutions.

The exemplar participants were also expected to show an increase in their solution times from transfer problem 1 to 2, reflecting additional cognitive processing for adapting their prior knowledge to the new problem. However, they were still predicted to have faster solution times than the no-training participants because they did not need to generate completely new procedures to solve the problem. The tactics participants were not expected to show a solution time advantage over the no-training group because, similar to problem 1, they needed to compile the tactics for a new set of problem features. The constraints participants were also not expected to show a solution time advantage because the constraint violation process requires multiple iterations.

Transfer problem 3.   For transfer problem 3 the exemplar participants were expected to show similar or worse performance on accuracy and solution time when compared to the no-training participants. This is because the exemplar knowledge no longer applies and could potentially interfere with problem solving and cause negative transfer (e.g., Luchins & Luchins, 1950). Tactics participants were also expected to show similar or worse performance compared to that of the no-training participants because the tactics did not directly apply to the pattern. However, the constraints group was expected to show higher accuracy than the no-training group because the constraints could be used to derive a correct solution.

Method and materials

Participants.   A total of 125 undergraduate students from the University of Illinois at Chicago subject pool participated in return for partial course credit.

TABLE 2
Training materials for each group

Training group	Materials	
a. Exemplars		
	Given String	*Solution*
1	L M Z M L Y M N X . . .	N M W N O V O N U
2	E F S F E R F G Q . . .	G F P G H O H G N
3	C D Q D C P D E O . . .	E D N E F M F E L
4	I J W J I V J K U . . .	K J T K L S L K R
b. Tactics summary		
1	First look for mirror flips or periods, this will help you break apart a pattern into its parts.	
2	When you see repeated letters in a sequence, check to see if they signal a mirror-flip (order of symbols), group repeat, or a period marker.	
3	When you see groups of letters that are *far* apart in the alphabet, check to see if they signal a mirror-flip (alphabet).	
4	When you see letters that are *close* together in the alphabet, check to see if they signal forward or backward relations.	
5	After you have identified the pattern and partitioned the sequence into groups of letters, then you can use those *pattern relations* to continue the sequence. Use the *relations identified* between the letter positions in each period of the given sequence to **generate** the letters that fill those same positions in each period of the continuation.	
c. Constraints summary		
1	*Six groups*: all letter strings MUST be divisible into six groups of letters.	
2	*Number of letters*: the number of letters in analogous letter groups MUST be the same.	
3	*Preceding group*: each letter group MUST be derived from an operation on the immediately preceding letter group or the letter group two back.	
4	*Order of operations*: the same order of letter operations MUST be used throughout the entire sequence. Operations must be repeated.	

Training materials. The *exemplar group* materials consisted of four[3] sequence extrapolation problem isomorphs. All four problems had the same structural relations but were instantiated with different objects (surface-level abstraction; see Table 2a for the exemplars).

The *tactics group* materials consisted of a tactics tutorial, summary sheet, and several blank recall sheets. The tutorial was 10 pages long and provided

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[3]Four was chosen as the number of exemplar problems because pilot work determined that the majority of the participants would solve at least two of them correctly, thus achieving the exemplar competence criteria for this experiment.

instruction on the specific kinds of pattern relations including: *forward*, *backward*, *identity*, *mirror-flip alphabet*, *mirror-flip order*, and *repeat*. Each relation was defined and multiple examples were given. The tutorial also provided two pages of instruction describing how to continue patterns once they are found. The summary sheet consisted of four pattern-finding tactics and one pattern-continuing tactic (see Table 2b for the tactics).

The *constraints group* materials consisted of a constraints tutorial, summary sheet, recall sheets, and a string violation worksheet. The tutorial was five pages long and provided instruction on the four letter pattern constraints (see Table 2c for the constraints). The string violation worksheet consisted of a series of completed letter strings that included both correct completions and those that violated one or more of the constraints.

Test materials.   The test tasks were three letter extrapolation problems. The first problem had a periodicity of three letters (see Figure 2). It had similar surface features and the same relational structure as the exemplar problems (surface-level abstraction). In addition, the tactics and constraint knowledge could be used to solve the problem. Participants were asked to continue the solution to six positions.

The second problem also had a periodicity of three letters. However, the correct continuation was ambiguous and was dependent on the interpretation of the given sequence. If the letters were parsed into cross period relations of *forward-1* and *backward-1* similar to those used in the exemplar problems, one solution type would be derived (see Figure 3, solution 1). Alternatively, if the given string was parsed into cross period relations of *mirror-flip alphabet* and *backward-1* relations as suggested by the deep analogy or pattern-finding tactic 3, a different solution would be derived (see Figure 3, solution 2). There were also three other solutions that followed the constraints (3 – XYMDELXYK, 4 – VWMDELTUK, 5 – ZAMDELBCK). Participants were asked to continue the solution to nine positions.
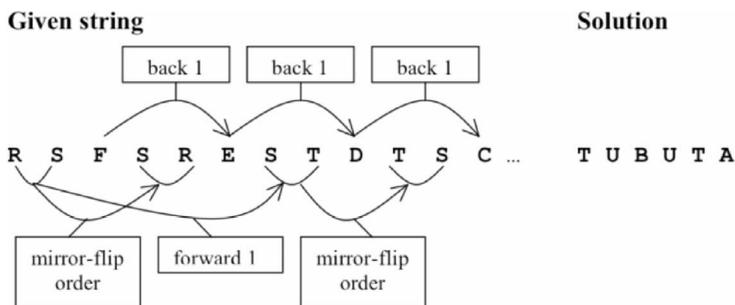

Figure 2. Transfer problem 1 with the relations identified and solution.
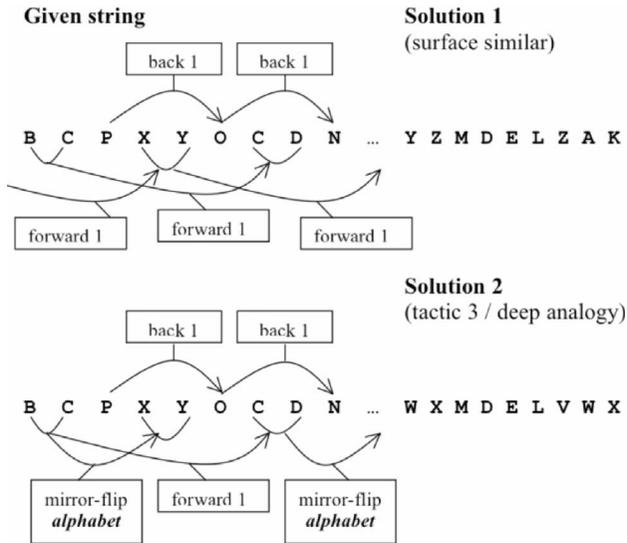
Figure 3. Transfer problem 2 with the relations identified for solutions 1 and 2.
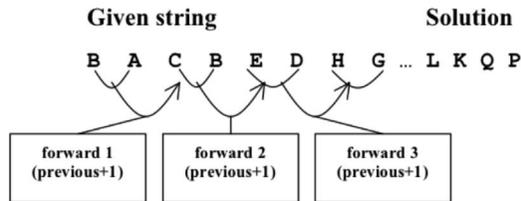
Figure 4. Transfer problem 3 with the relations identified and solution.

The third problem had a periodicity of two letters and had neither surface nor deep structure similarity to the exemplar problems (see Figure 4). In addition, there was no pattern-finding tactic that applied directly to the iterative nature of the pattern. However, a unique solution could be derived by constraint violation. The pattern consisted of letter pairs incrementally increasing through the alphabet with each pair skipping an additional letter as the pattern progressed. Participants were asked to continue the solution to four positions.

Transfer problems were presented on a Macintosh computer with a 20-inch colour monitor, standard keyboard, and mouse. Problems were presented in black 30-point font in the centre of the screen. The transfer portion of the experiment was designed and presented using PsyScope software (Cohen, MacWhinney, Flatt, & Provost, 1993).

Design. A between-participants design was used with participants randomly assigned to one of four conditions: *exemplar training* ($n = 31$), *tactics training* ($n = 31$), *constraints training* ($n = 33$), and *no-training* ($n = 30$). Participants were tested individually and the procedure consisted of a training and test phase.

Training for the exemplar group. Participants were given 3 minutes to solve the first training problem. Next, they received feedback on each position of their solution. If any position was incorrect they were given another instance of the same problem and 3 minutes to solve it. This cycle continued until the problem was solved correctly or the participant made four attempts. This procedure was repeated for the remaining three training problems.

Training for the tactics group. Participants first read the tactics tutorial and then were given 3 minutes to memorise the tactics summary sheet. Next, they completed an unrelated distractor task (i.e., three arithmetic problems) followed by tactics recall. If they omitted or incorrectly recalled any of the tactics they were given another 2 minutes to study the summary sheet followed by another distractor task and recall. This cycle was continued until the participants recalled all five tactics. Next, they explained each tactic to the experimenter. If they gave an incorrect explanation the experimenter provided the correct one.

Training for the constraints group. Participants first read the constraints tutorial and then were given 3 minutes to memorise the constraints summary sheet. Next, they completed a distractor task (similar to tactics training) followed by constraints recall. If they omitted or incorrectly recalled any of the constraints they were given 2 minutes to study the summary sheet again, followed by another distractor task and recall. This cycle continued until they recalled all four constraints. Participants then explained each constraint to the experimenter. If they gave an incorrect explanation the experimenter provided the correct one. Participants then completed the string violation worksheet and were given feedback on their performance.

Training to criterion. Participants in all three groups were trained to a performance criterion. This ensured that each participant learned his or her respective training knowledge. The criterion for the exemplar group was solving at least two of the training problems correctly. The criterion for the tactical and constraints groups was complete recall of the tactics and constraints respectively. All but three participants in the constraints group and one participant in both the exemplar and tactical groups passed the

criterion. These participants were excluded from further analysis leaving 30 participants ($n = 30$) in each training group.

No-training group.   Participants in this condition did not receive any training and served as a comparison condition for baseline performance on the transfer tasks.

Test phase.   Participants were told that they were to solve three extrapolation test problems. They were reminded that their training might help them solve the problems and were presented each problem one at a time in the same presentation order. They were given 6 minutes to solve each problem with a warning when they had a minute left.

Results

To assess transfer, multiple measures of problem solving were collected, including accuracy, solution type, and time to solution. Alpha was set to .05 for all main effects and interactions, and Bonferroni corrections were used for all planned comparisons setting alpha to .01 (Keppel, 1991). Effect sizes (eta squared, η^2) were calculated for main effects, interactions, and main comparisons. Cohen (1988; see also Olejnik & Algina, 2000) has suggested that effects be regarded as small when $\eta^2 < .06$, as medium when $.06 < \eta^2 < .14$ and as large when $\eta^2 > .14$.

Accuracy performance.   Accuracy performance was used to examine the effect of training on participants' competence in solving the three transfer problems. Participants' *accuracy scores* were based on the proportion of solution positions correctly extrapolated for each transfer problem. Each

TABLE 3
Proportion of correct extrapolations, standard errors, and standardised mean difference scores for each group across transfer problems

	Transfer 1		Transfer 2		Transfer 3	
Training group	*Prop. correct M SE*	*Effect δ*	*Prop. correct[a] M SE*	*Effect δ*	*Prop. correct M SE*	*Effect δ*
Exemplar	**.93*** (.04)	1.90	.80 (.05)	.35	.21 (.07)	−.20
Tactics	**.78*** (.06)	1.10	.72 (.06)	.11	.22 (.07)	−.18
Constraints	**.70*** (.06)	.85	.73 (.06)	.14	.26 (.08)	−.08
No-training	.40 (.07)		.69 (.07)		.29 (.08)	

*Significantly different from no-training, $p < .01$; [a]correct solutions for transfer 2 included any of the five possible solution types.

training group's mean accuracy scores, standard errors, and standardised mean difference scores are presented in Table 3.

A 4 (training) × 3 (transfer problem) mixed ANOVA was conducted to investigate the effect of training on accuracy across the transfer problems. Analysis revealed a medium-sized main effect for training, $F(3, 116) = 2.70$, $p < .05$, $\eta^2 = .07$, and a large main effect of transfer problem, $F(2, 232) = 104.30$, $p < .05$, $\eta^2 = .47$. These effects were qualified by a medium-sized interaction of training by transfer problem, $F(6, 232) = 6.23$, $p < .05$, $\eta^2 = .13$. The interaction is best explained by the large advantage of the training groups over the no-training group on transfer problem 1, but not on problems 2 and 3. Follow-up comparisons for transfer problem 1 revealed that the exemplar, tactics, and constraints groups all performed better than the no-training group, $F(1, 116) = 43.54$, $p < .01$, $\eta^2 = .21$, $F(1, 116) = 21.85$, $p < .01$, $\eta^2 = .12$, and $F(1, 116) = 13.78$, $p < .01$, $\eta^2 = .08$ respectively. In contrast, there were no differences between the training and no-training groups on problems 2 and 3, $F(3, 116) = .60$, ns and $F(3, 116) = .27$, ns respectively.

As predicted, the exemplar, tactics, and constraints groups all performed significantly better than the no-training group on transfer problem 1 showing strong evidence for knowledge transfer. The training groups also showed high-level performance on transfer problem 2 but did not show a significant improvement over the no-training group. However, differences were expected for the types of solutions each group would generate and are examined in the next section. Finally, although the constraints group showed high accuracy on the first two transfer problems they did not show the expected high accuracy performance on transfer problem 3. Either these participants did not attempt to use their prior knowledge to solve the problem or tried and failed, possibly due to processing limitations (see the discussion section).

Solution type for problem 2.   In the previous analysis both the training and no-training groups showed high-level performance on transfer problem 2 ranging from 69% to 80% mean accuracy. In this section, I examine whether differences emerge for the *types* of solutions that each group used to solve the problem.

Although there were five possible solutions, specific predictions were only made for solution types 1 and 2 (see Figure 3). The participants given exemplar training were expected to show a bias for generating *solution 1* because of the surface-level matches to the exemplar problems. In contrast, the participants given tactics training were expected to show a bias towards generating *solution 2* because their tactical knowledge applied directly to this pattern interpretation. Finally,

the participants given constraints training were predicted to generate solutions similar to those of the control participants because knowledge of the constraints did not provide an a priori bias to any one of the five plausible solutions.

A classification protocol was used to categorise each solution. For a solution to be classified as one of the five solution types, it must have had an overall high accuracy as well as the *characteristic solution features* unique to that solution type.[4] For example, the characteristic features for solution 1 are YZ and ZA. If the candidate solution could not be unambiguously classified as one of the five solution types it was labelled as *unclassified*. The proportion of participants in each group to use each solution type is presented in Table 4.

Chi-square tests show that the training groups differed significantly in the number of participants to use a particular solution type, $\chi^2(9, N = 120) = 37.99$, $p < .05$. Of particular interest is whether the groups differed in their use of solutions 1 and 2. Comparisons revealed that the participants in the exemplar group used solution 1 significantly more than the participants in the tactics, constraints, and no-training groups, $\chi^2(1, N = 60) = 13.61$, $p < .01$, $\chi^2(1, N = 60) = 3.27$, $p < .10$, and $\chi^2(1, N = 60) = 6.70$, $p < .01$, respectively. In addition, more participants from the constraints group used solution 1 than in the tactics group, $\chi^2(1, N = 60) = 4.02$, $p < .10$. Furthermore, significantly more participants used solution 2 from the tactics group than in the exemplar, constraints, and no-training groups, $\chi^2(1, N = 60) = 11.82$, $p < .01$, $\chi^2(1, N = 60) = 11.82$,

TABLE 4
Proportion of participants using each solution type from each group

Training group	Solution 1 (surface similar)	Solution 2 (tactics / deep analogy)	Solution 3–5	Unclassified
Exemplar	**63%***	3%	3%	30%
Tactics	17%	**40%***	17%	26%
Constraints	40%	3%	13%	43%
No-training	30%	0%	26%	43%

*Significantly different from no-training, $p < .01$.

[4]A second classification scheme that was based on 100% accuracy revealed the same pattern of results. I used the classification scheme reported here because it can classify more of the data, particularly for those solutions with one or two incorrect extrapolations but with the characteristic solution features.

$p < .01$, and $\chi^2(1, N = 60) = 15.00$, $p < .01$, respectively. The remaining groups did not significantly differ in their use of solution 2.

These results provide strong evidence that the exemplar and tactics participants used training knowledge to solve the transfer problems. The exemplar group showed a preference for the surface similar solution, whereas the tactics group showed a preference to use the tactics relevant solution. In addition, the constraints group did not differ from the no-training group as to the number of participants to use each solution type. These results are consistent with the predictions for each of the three mechanisms.

Solution time. Participants' *solution time* was the total time in seconds to solve the problem. Solution times were calculated for each participant regardless of whether they solved the problem correctly. Each training group's mean solution times and standard errors for the three transfer problems are presented in Table 5a.

A 4 (training) × 3 (transfer problem) mixed ANOVA was conducted to investigate the effect of training on participants' solution times for each transfer problem. The analysis revealed a medium-sized main effect for training, $F(3, 116) = 4.92$, $p < .05$, $\eta^2 = .11$, and a large main effect of transfer problem, $F(2, 232) = 26.21$, $p < .05$, $\eta^2 = .18$. These effects were qualified by a medium-sized interaction of training by transfer problem, $F(6, 232) = 3.42$, $p < .05$, $\eta^2 = .08$. The interaction is best explained by the faster solution time of the exemplar group over all other groups on problem 1, $F(3,$

TABLE 5
Mean solution times (seconds) and standard errors for each training group across the transfer problems

Training group	Transfer 1		Transfer 2		Transfer 3	
a. Overall						
	M	*SE*	*M*	*SE*	*M*	*SE*
Exemplar	**108***	(13)	206	(17)	250	(16)
Tactics	221	(19)	245	(16)	289	(17)
Constraints	217	(17)	234	(20)	244	(16)
No-training	216	(20)	242	(17)	268	(16)
b. Participants with 100% accuracy						
	M	*n*	*M*	*n*	*M*	*n*
Exemplar	**97***	26	**153***	15	188	4
Tactics	191	19	222	13	291	6
Constraints	192	15	223	14	241	7
No-training	194	6	222	15	243	7

*Significantly different from no-training, $p < .01$.

$116) = 28.87$, $p < .01$, $\eta^2 = .20$, but not on problems 2 and 3, $F(3, 116) = 1.06$, *ns* and $F(3, 116) = 1.53$, *ns* respectively. These results suggest that participants given exemplar training transferred prior knowledge of the declarative pattern as well as the extrapolation procedures.

One potential critique of this analysis is that the differences in solution times may have been driven by mean differences in accuracy across the training groups. However, as Table 5b shows, a similar pattern of results was obtained for those participants who had 100% accuracy. These results support those found in the entire sample showing that the exemplar group solved transfer problem 1 much faster than the other training groups. In addition, these participants also showed a significant solution time advantage for problem 2.

Discussion of Experiment 1

All three training groups showed a large accuracy advantage over the no-training group on the first transfer problem. This result suggests that the application conditions for all three mechanisms were satisfied for this problem. Specifically, the exemplar knowledge had similar surface features and the same structural relations, the tactics were relevant, and the constraints applied to this problem. Although this result shows that the training knowledge facilitated problem-solving performance, it does not address how this knowledge was used to solve the problem. To understand how the knowledge was used, I turn to the solution times for a processing account.

The exemplar participants solved problem 1 much more quickly than the other groups, suggesting that they transferred both declarative and procedural knowledge. In contrast, the tactics group had long solution times similar to the no-training group, suggesting that they had to compile or articulate their prior knowledge in order to solve the problem. Similarly, the constraints group also had long solution times, suggesting that constraint violation requires multiple iterations to produce the correct solution.

On the second transfer problem the training groups had similar accuracy scores to that of the no-training group. However, evidence of knowledge transfer comes from the types of solutions used to solve the problem. The exemplar participants generated more surface-similar solutions, suggesting that they used a surface analogy to their prior exemplar knowledge whereas the tactics participants generated more tactics-relevant solutions. In addition, the constraints participants' solution types were not significantly different from the control, suggesting that the constraints knowledge did not bias them towards any one of the solution types.

The exemplar group also took longer to solve this problem than the first transfer problem. This suggests that these participants had to engage in additional cognitive processing to adapt their prior knowledge to the change in surface feature/deep structure alignment of the problem. The tactics and constraints participants had long solution times similar to the no-training group, suggesting that they also had to engage in significant amounts of cognitive processing to generate the correct solution.

All three training groups performed poorly on the third transfer problem. Although this result was expected for the exemplar and tactics groups (because their training knowledge did not apply to this pattern), it was unexpected for the constraints group, since their knowledge was relevant for the problem. It is possible that these participants attempted to use constraint violation but were not able to derive the correct solution due to problem difficulty and working memory limitations.[5] This hypothesis is investigated in the next experiment via examination of participants' verbal protocols. If participants were using knowledge of the constraints and error correction to solve the problem this should be exhibited in their problem-solving protocols.

In sum, the results from this experiment provide support for the hypothesis that there are multiple mechanisms of transfer that are distinct and identifiable. Participants in three separate transfer scenarios exhibited behavioural patterns of performance consistent with those predicted by the three theories of knowledge transfer for two out of the three transfer problems. The next question is whether these mechanisms interact when a person has all three prior knowledge structures. If multiple mechanisms can be used in a given situation, will people use the optimal or most efficient one (i.e., the mechanism whose application conditions apply and requires the least amount of cognitive effort)?

EXPERIMENT 2: INVESTIGATING THE ADAPTIVE SHIFTING HYPOTHESIS

Although Experiment 1 provides evidence that there are multiple mechanisms of transfer that are triggered in particular learning and problem-solving situations, the question of how these mechanisms interact is left unanswered. The purpose of this experiment was to train participants on all three types of prior knowledge and then assess whether or not they shift between mechanisms depending on the characteristics of the transfer tasks.

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[5]Problem 3 required participants to make substantially larger letter calculations than problems 1 and 2 (e.g., forward-5 versus forward-2). This may have caused difficulty in generating the correct extrapolation inferences as well as retrieving the appropriate letters for those inferences.

It was hypothesised that different mechanisms would be triggered in different transfer scenarios depending on one's prior knowledge and the properties of the transfer task. Three transfer hypotheses were investigated: (1) analogical transfer occurs when the transfer task has corresponding surface and deep structure similarity to that of the exemplar problem; (2) knowledge compilation occurs if the transfer task does not trigger prior exemplar knowledge or there is an inconsistent mapping (i.e., different surface/deep structure alignment), but one's tactical knowledge is relevant and accessible; and (3) constraint violation occurs if the transfer task does not trigger either tactics or exemplar knowledge (i.e., no surface or deep pattern similarity and the tactics do not appear relevant), but the general constraints for the domain are applicable.

To test these hypotheses, I implemented a within-participants design in which each participant received all three of the training scenarios used in Experiment 1, including exemplars, tactics, and constraints training. After training, participants were given the same three test tasks and were instructed to "think aloud" while problem solving. Below I describe the behavioural predictions for the training group across the three transfer problems (see Table 6 for a summary).

Predictions

Transfer problem 1. Participants were expected to use analogy because there are both surface and deep structure matches to their prior exemplar knowledge. They should use analogy instead of tactics and knowledge compilation because the exemplar knowledge requires less adaptation to solve the problem (i.e., the same pattern and extrapolation procedures). In contrast, if participants use tactics and knowledge compilation, they must figure out the pattern as well as the action implications for extrapolating that pattern. Similarly, participants are expected to use analogy instead of constraint violation because the latter requires more cognitive processing (see solution times, Table 5 problem 1).

TABLE 6
Transfer problem predictions for the training group relative to the no-training group

Measure	Transfer 1	Transfer 2	Transfer 3
Problem solving	**High accuracy** **Fast solution times**	**Similar accuracy** **Bias to tactics solution** **Similar solution times**	**High accuracy** **Similar solution times**
Verbal protocols	**Statements of analogy**	**Statements of tactics**	**Statements of constraints & error checking**

Predicted results in bold differ from those expected for the no-training group.

It is predicted that participants will show the same behavioural profiles for analogical transfer as those found for the exemplar group in Experiment 1, including high accuracy and fast solution times when compared to the no-training group. In addition, participants were expected to make statements of analogy in their think aloud protocols.

Transfer problem 2. Participants were expected to use tactics and knowledge compilation to solve transfer problem 2. They should use knowledge compilation instead of analogy because the surface and deep structure are misaligned with the exemplar problems. Since the critical relations have changed (mirror-flip order to mirror-flip alphabet), lowering the overall surface similarity, participants are expected to shift to tactics because they are directly applicable to the surface features of the problem (i.e., "*letters far apart in the alphabet*"). Participants should use knowledge compilation instead of constraint violation because the tactics offer a more direct route to pattern identification. In contrast, the constraint violation process requires several iterations of general problem solving, constraint checking, and error correction—a time-intensive process that can only lead to a correct solution through a successive refinement of procedures. Participants were expected to show high accuracy and similar solution times to that of the no-training group, as well as exhibit evidence of tactics application in their verbal protocols.

Transfer problem 3. Participants were expected to use constraint violation to solve this transfer problem because it does not have surface or deep structure similarity to the exemplar problems, nor do any of the tactics directly apply. Similar to Experiment 1, participants were expected to show low to moderate accuracy with long solution times. Importantly, participants' verbal protocols were expected to exhibit application of the constraints and error checking.

Method and materials

Participants. A total of 48 undergraduate students from the University of Illinois at Chicago subject pool participated in return for partial course credit.

Training materials. The training materials consisted of three parts: exemplars, tactics, and constraints. These materials were the same as those used in Experiment 1 (see Table 2). The presentation order was counter-balanced, producing six versions of training. There was also a final review section that consisted of the summary materials from each of the training sections.

Test materials.   The transfer tasks were the same as Experiment 1 (see Figures 2–4). In addition, there was a post-test questionnaire.

Design.   A within-participants design was used with participants randomly assigned to one of the six training orders ($n \sim 6$ given each order, for a total of 38 training participants). In addition, a no-training control group was used as a comparison of baseline performance ($n = 10$). The problems were presented in two orders: half of the participants received the transfer problems in the same order as Experiment 1, and the other half received the reverse order. Participants were trained and tested individually.

Training phase.   The training phase was divided into three sections: constraints, tactics, and exemplars. In each section participants followed the same procedure as the corresponding training groups from Experiment 1. After completing all three sections, there was a 1-minute break followed by a 3-minute review of the summary materials.

Training to criterion.   The same performance criterions from Experiment 1 were used, to ensure that each participant had learned the training knowledge. All but two participants passed the criteria. These participants were excluded from further analysis leaving 36 participants in the training group.

No-training group.   Participants in this condition did not receive any training.

Test phase.   Participants were instructed to think aloud while they solved the three transfer problems. They were presented the problems one at a time and were given 8 minutes to solve each one. After the test phase participants were given a brief post-test questionnaire to complete.

Results

The results are divided into two sections. In the first section, I assess transfer performance using the same problem-solving measures as used in Experiment 1 including accuracy, solution types, and time to solution. In the second section, I examine participants' verbal protocols focusing on the number of participants to make statements implicating each transfer mechanism across the three problems. Initial analyses revealed no effects or interactions for the order of training or test materials and all subsequent analyses collapsed across these groups.

Section 1: Transfer performance – problem-solving measures

Accuracy performance. The participants' accuracy score was calculated as in Experiment 1. The training and no-training group's mean accuracy scores, standard errors, and standardised mean difference scores for each transfer problem are presented in Table 7a.

A 2 (training) × 3 (problem) mixed ANOVA was conducted to investigate the effect of training on accuracy across the transfer problems. The analysis revealed a large effect for transfer problem, $F(2, 88) = 61.27$, $p < .05$, $\eta^2 = .58$, indicating that the overall accuracy differed across the transfer problems. There was also a medium-sized effect of training, $F(1, 44) = 7.04$, $p < .05$, $\eta^2 = .14$, indicating that the training group had an overall higher accuracy than the no-training group. There was no interaction of problem by training, $F(2, 88) = 1.58$, *ns*. Follow-up comparisons for the effect of transfer problem revealed that participants' accuracy performance was considerably lower on problem 3 as compared to problems 1 and 2, $F(1, 45) = 99.45$, $p < .01$, $\eta^2 = .69$, and $F(1, 45) = 123.25$, $p < .01$, $\eta^2 = .73$ respectively. These results show that the training participants performed significantly better on accuracy than the no-training participants.

Solution type for transfer problem 2. Although the training and no-training groups both showed high accuracy performance for problem 2, only the training participants were expected to show a bias towards *solution 2*, because their tactical knowledge applied directly to this pattern

TABLE 7

Mean accuracy and solution times with standard errors for each group across the transfer problems

Group	Transfer 1			Transfer 2			Transfer 3		
a. Accuracy									
	Prop. correct		Effect	Prop. correct		Effect	Prop. correct		Effect
	M	*SE*	*δ*	*M*	*SE*	*δ*	*M*	*SE*	*δ*
Training*	**.86**	(.05)	.80	**.85**	(.03)	.05	**.22**	(.06)	.73
No-training	.63	(.10)		.85	(.05)		0	(0)	
b. Solution times (seconds)									
	M	*SE*		*M*	*SE*		*M*	*SE*	
Training (overall)	**121***	(15)		221	(20)		298	(26)	
Training (100% acc.)	**103***	(8)		208	(20)		257	(66)	
No-training	221	(52)		204	(34)		312	(33)	

*Significantly different from no-training, $p < .01$.

interpretation (see tactic 3, Table 2b). The proportion of participants to use each solution type is presented in Table 8.

Chi-square tests show that the groups significantly differed in the number of participants to use a particular solution type, $\chi^2(3, N = 46) = 9.10$, $p < .05$. In particular, more training participants used solution 2 (the tactics relevant solution) than those given no training, $\chi^2(1, N = 46) = 8.99$, $p < .01$, indicating that participants used tactics knowledge to solve the problem. This is also consistent with the results obtained in Experiment 1, showing that participants trained on exemplars were biased to use solution 1 whereas participants trained on tactics were biased to use solution 2.

Solution time. The training and no-training groups' mean solution times and standard errors on each transfer problem are presented in Table 7b. A 2 (training) $\times$ 3 (problem) mixed ANOVA was conducted to investigate the effect of training on solution times across the transfer problems. The analysis revealed a large main effect of transfer problem, $F(2, 88) = 12.12$, $p < .05$, $\eta^2 = .21$, indicating that the overall solution times differed across the transfer problems. There was no main effect for training, $F(1, 44) = 1.05$, $MSE = 23,644$, *ns*. However, there was a marginal interaction of training by transfer problem, $F(2, 88) = 2.47$, $p = .09$, $\eta^2 = .05$.

A simple effects analysis of training shows an effect for problem 1, $F(1, 44) = 6.45$, $p = .015$, $\eta^2 = .13$, but not problems 2 and 3, $F(1, 44) = .17$, *ns* and $F(1, 44) = .06$, *ns* respectively. The training participants were much faster than the no-training group on transfer problem 1 but not on problems 2 and 3. This result is consistent with that found in Experiment 1, suggesting that training participants transferred procedural knowledge from the exemplars to solve problem 1. In addition, the training group showed significant solution time increases from problems 1 to 2, $F(1, 35) = 20.40$, $p < .01$, $\eta^2 = .37$, and from problems 2 to 3 $F(1, 35) = 10.99$, $p < .01$, $\eta^2 = .24$, reflecting increases in participants' cognitive processing across the problems. The same pattern of results was observed for those participants with 100% accuracy (see Table 7b).

TABLE 8
The proportion of participants classified as using each solution type

	Solution type			
Group	Solution 1 (surface similar)	Solution 2 (tactics/deep analogy)	Solutions 3–5	Unclassified
Training	19%	**53*%**	17%	11%
No-training	40%	0%	40%	20%

Section 2: Analysis of verbal protocols

Coding procedures and reliability.   The verbal protocols were transcribed from audio files into statements. The statement length was determined by clauses and natural breaks in the protocol. Two independent coders then classified each statement according to a predetermined classification scheme based on a task analysis of the cognitive processes used in sequence extrapolation tasks.[6] For the purposes of the current article I focus on the codes used to assess the specific transfer processes of analogy, tactics use, constraint application, and error correction.

The *analogy* codes were used to classify statements of comparison or mapping from the exemplar problem and its features to the transfer problem and vice versa. The *tactics* codes were used to classify statements for the search and identification of tactical pattern relations such as forward or backward relations, repetitions, and mirror flips. The *constraints* codes were used to classify statements of constraint application and evaluation. There was also a code for general *error checking* which was used to classify statements of checking or evaluating a current or a previous problem solving state. See Table 9 for verbal protocols showing examples of each.

The two coders classified a total 4134 statements, resulting in a total of 5281 codes. The coding reliability was calculated as the percent agreement between the two coders. Reliability scores across participants ranged from 79% to 96% agreement. Total percent agreement across all training and control participants was 87%.

Protocol measure.   A summary measure for the *number of participants* to have protocol evidence implicating the use of each transfer mechanism was assessed across the three transfer problems. To assess whether or not each participant used a particular mechanism, the number of statements they generated for each mechanism was assessed (i.e., the *statement score*). If a participant's score for a particular transfer mechanism was above the average score of the no-training group, she or he was classified as showing evidence for using that mechanism. Comparing participants' scores to the average of the no-training scores separates the effects from training from those expected from normal problem solving. The number of participants classified as showing evidence for each transfer mechanism across the problems is presented in Table 10.

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[6]The candidate processes were drawn in part from past work on sequence extrapolation (Greeno & Simon, 1974; Klahr & Wallace, 1970; Nokes & Ohlsson, 2003, 2005; Simon, 1972; Simon & Kotovsky, 1963).

TABLE 9
Example verbal protocol evidence for analogy, tactics, constraints, and error checking

Mechanism		Participant	Protocol	Code(s)
Analogy	S-11	11	F ok so F and then it's R RSSR ST TS ok	parsing
		12	**RS SR ST is the same sequence on the ... same sequence on the sheets**	**analogy***
		13	S RSSR T TS	parsing
Tactics	S-24	1	ok BCPXYOCDN	reading given
		2	**hmm ... BC and then it's mirror image XY**	**tactics***
		3	**and then that's a mirror C D**	**tactics***
		4	PON ... NOP right	parsing
Constraints	S-17	10	hmm I don't see a pattern so far	comment
		11	BA CB	parsing
		12	**there has to be six**	**constraints***
		13	**there has to be two letters in a group**	**constraints***
		14	ok I don't see any mirror flips	tactics
Error checking	S-3	25	BA AB	Parsing
		26	**AB or is it BAC BED no**	parsing, **error checking***
		27	um three, three, three	counting

TABLE 10
The number of participants to show protocol evidence for each transfer mechanism

	Transfer mechanism			
Transfer problem	Analogy	Tactics	Constraints	Error checking
1	**4**	15	7	7
2	1	**21**	13	16
3	0	14	**17**	**23**

A Cochran's Q test was used to examine the number of participants to exhibit verbal data implicating use of the different mechanisms across the transfer problems. Because some mechanisms may be less likely than others to show up in the verbal protocols, two types of analyses were conducted. First, I examined for each problem which mechanism was used the most. Second, I examined for each mechanism which problem it was used the most on. This analysis assesses the *relative use* of each mechanism across the problems.

For transfer problem 1 more participants used tactics than analogy, constraints, or error checking, $Q(3, N = 36) = 11.95$, $p < .05$. However, there was a relative shift for more participants to use analogy on problem 1 than on problems 2 and 3, $Q(2, N = 36) = 6.50$, $p < .05$. On transfer problem 2 more participants used tactics than analogy, constraints, and error checking, $Q(3, N = 36) = 32.46$, $p < .05$. In addition, there was a marginally significant shift for more participants to use tactics on problem 2 than on problems 1 and 3, $Q(2, N = 36) = 4.30$, $p = .10$. Finally, on transfer problem 3 more participants used error checking than tactics or analogy, $Q(3, N = 36) = 29.46$, $p < .05$. In addition, there was a relative shift for more participants to use constraints and error checking on problem 3 than on problems 1 and 2, $Q(2, N = 36) = 8.94$, $p < .05$; $Q(2, N = 36) = 10.30$, $p < .05$ respectively. These results show that the proportion of participants to use of each transfer mechanism shifts across the transfer problems. However, these shifts were only relative, some participants used multiple mechanisms for a given problem and others used the non-optimal mechanism.

Discussion of Experiment 2

Training participants showed high accuracy performance and fast solution times on problem 1. The accuracy advantage over that of the no-training group is consistent with the interpretation that any of the three types of prior knowledge facilitated performance. However, participants' solution times were much faster than the no-training group, suggesting transfer of procedural knowledge from the exemplar problems.

As predicted, more participants made statements of analogy on transfer problem 1 than on the other two transfer problems. However, fewer participants than expected made statements of analogy and more participants made statements of tactics for this problem. One explanation for the lack of analogy statements is that the relations may have been perceived as highly salient and therefore not necessary to map explicitly. Some support for this explanation comes from the post-test questionnaires where participants rated the similarity of the test problems to the exemplars on a 1 "Low Similarity" to 5 "High Similarity" Likert scale. Participants rated problem 1 as highly similar ($M = 4.54$, $SE = .13$), problem 2 as moderately similar ($M = 3.45$, $SE = .18$), and problem 3 as having low similarity ($M = 1.77$, $SE = .19$) to the exemplar problems, showing that participants were sensitive to the overall similarity between the problems.

For transfer problem 2, although the training participants showed similar accuracy scores to that of the no-training group, evidence for the tactical shift hypothesis comes from the fact that the training group used the *tactics-relevant solution* more than the no-training group. In addition, training participants' solution times were significantly longer for transfer problem 2

than transfer problem 1, suggesting that the participants needed time to compile their tactics knowledge to solve the problem. Finally, more participants made statements of tactics than analogy and constraints, showing that participants used primarily tactics knowledge to solve this problem.

Participants showed a significant accuracy advantage over the no-training group on transfer problem 3. In addition, their solution times were significantly longer for this problem than for problem 2, which suggests that extensive cognitive processing was necessary to solve the problem. Strong evidence for a shift to constraint violation comes from the fact that more training participants made statements of constraints and error checking for this problem than for problems 1 and 2.

The results from this experiment show that people shift between transfer mechanisms depending on their prior knowledge and the characteristics of the transfer tasks. In particular, the results provide support for the hypotheses that participants: (1) show a relative shift to using analogy and exemplar knowledge to solve the transfer tasks that have similar surface and deep structure matches to their exemplar knowledge, (2) show a relative shift to using tactics and knowledge compilation when their exemplar knowledge is no longer accessible (even though there may be deep structural similarity), and (3) show a relative shift to using constraint violation when they encounter a problem that does not prompt exemplar knowledge and tactics are no longer relevant. In addition, the results show that the use of each transfer mechanism was not all or none, and in some cases participants used a mix of transfer mechanisms.

GENERAL DISCUSSION

Towards a general theory of transfer

A central goal of the current work was to attain a better understanding of the cognitive processes used in knowledge transfer and to identify the properties associated with the types of knowledge and situations in which those processes are invoked. Experiment 1 tested the predictions of analogy, knowledge compilation, and constraint violation within the same experimental paradigm. Each mechanism was shown to predict specific behavioural patterns of performance under particular transfer conditions. Experiment 2 examined how these mechanisms interact, and showed that people are capable of adaptive shifting between multiple mechanisms depending on their prior knowledge and specific characteristics of the transfer task.

The results from Experiment 2 suggest that each transfer mechanism's applicability is bound by the fit between what knowledge is available (in the

mind of the learner) and the characteristics of the transfer environment. In particular, there is a trade-off between applicability and efficiency for each mechanism. Analogy is fast and efficient to the degree that the current situation matches prior exemplar surface features and deep structure. More dissimilar matches require additional cognitive work to apply that knowledge (i.e., representational re-description or structural adaptation) and make one more likely to shift to another transfer mechanism. The more one's prior exemplar knowledge does not match the current situation, the more likely one is to shift to knowledge compilation of applicable declarative knowledge.

Knowledge compilation in turn has wide applicability but requires a lengthy application procedure. Because of this lengthy interpretation process, knowledge compilation will only be triggered when one has no accessible exemplar knowledge or when the exemplar requires extensive adaptation in order to be applied. The degree to which declarative instructions or strategies are no longer applicable to the task determines the likelihood that one will shift to constraint violation. Constraint violation also has wide applicability as defined by the constraint principles for a particular domain. Although constraint violation has wide applicability and can produce novel strategies, it also requires significant cognitive processing and revising of past incorrect attempts to derive a correct solution. Therefore, constraint violation will only be triggered when one has no accessible exemplars and tactical knowledge does not apply.

It is important to note that these are relative shifts in application and that people often use a mixture of multiple transfer processes for a given situation. Therefore, what changes is the relative mix or proportion of transfer processes triggered depending on the characteristics of one's prior knowledge and the task environment. This theory of multiple mechanisms and adaptive shifting is essentially a cognitive economy theory of transfer. A given mechanism is triggered to the degree that its utility is optimised based on the current knowledge of the learner and the properties of the task. The selected mechanism is the one that requires the least amount of cognitive work or effort to achieve the desired results (i.e., it yields the highest utility).

The importance of multiple measures for assessing transfer

In addition to developing a framework for a general theory of transfer, this work also exemplifies the importance of using multiple measures and tasks to assess transfer. If only one of the dependent measures had been used in the current experiments, radically different conclusions would have been made, drastically underestimating the amount and kind of transfer. For example, if only accuracy performance was

assessed on transfer problem 2, one could not have concluded that transfer even occurred, much less differentiated between the different mechanisms.

Bransford and Schwartz (1999), Lave (1988), Lobato (2006), and others have critiqued "classical" assessments of transfer as being too narrow and focusing primarily on the direct application of prior knowledge in problem solving scenarios. For example, consider the following critique (Lobato, 2006, p. 434):

> ... classical transfer studies privilege the perspective of the observer and rely on models of expert performance, accepting as evidence for transfer only specific correspondences defined a priori as the 'right' mappings.

And from Bransford and Schwartz, (1999, p. 68):

> There are no opportunities for them [the participants] to demonstrate their abilities to learn to solve new problems by seeking help from other resources such as texts or colleagues or by trying things out, receiving feedback, or getting opportunities to revise.

The current approach advocates the use of multiple measures of transfer (accuracy, solution types, time to solution, verbal protocols, etc.) as one remedy to the overly narrow classical assessment methodology. It is important to provide several measures across a variety of tasks, not just a single measure (i.e., success or failure) for a single task. Using multiple assessment measures and tasks enables the researcher to capture the dynamic, constructive nature of transfer. By using such an approach one can assess both *what* knowledge is transferred as well as *how* that knowledge is transferred.

Understanding transfer and organising the literature

Past attempts to understand transfer have been focused on determining the contexts that facilitate transfer (e.g., Gick & Holyoak, 1987; Mestre, 2003). One recent attempt to organise and understand the transfer literature by Barnett and Ceci (2002) provides an example of this approach. The authors provided a detailed analysis and organisation of the transfer literature by categorising past studies by the type of transfer contexts investigated (i.e., knowledge domain, physical context, temporal context, functional context, social context, and modality). Although this approach is an important step forward in describing contexts that facilitate transfer, the current work suggests that there are two factors missing from this analysis that are critical to understanding transfer. These include the *type of knowledge* transferred and the *mechanisms or processes used to transfer* that knowledge.

Although Barnett and Ceci explicate some important differences in the contents of prior knowledge, they primarily discuss the specificity-versus-generality characteristics of the to-be-transferred skill. The current work suggests that there are other important differences that should also be taken into account, such as whether the knowledge is exemplar, instructional, or constraint based. In addition, the authors do not make a principled distinction between declarative versus procedural knowledge, an important factor that the current results show has a large effect on what and how the knowledge is transferred. The second critical factor is that there are multiple mechanisms of transfer. Understanding when these mechanisms are triggered is essential to how we make sense of the prior empirical work.

Multiple reviews have pointed out that the transfer literature exhibits a mixture of both positive and negative results (Bransford & Schwartz, 1999; Detterman & Sternberg, 1993; Lobato, 2006; Salomon & Perkins, 1989). It is proposed here that greater clarity might result if we assume that different transfer processes are triggered in different types of transfer scenarios. Results from the current study show that different transfer mechanisms predict different behavioural patterns for different types of transfer tasks. To understand transfer we must assess one's prior knowledge and the characteristics of the transfer task to determine what types of behaviours to expect. A survey of the literature may find that the particular experimental paradigms used did not employ the proper measures or task environments to assess the type of transfer expected for that situation. Taking a multiple mechanisms perspective suggests that to understand transfer one must examine several interrelated aspects of the transfer scenario, not just one or two variables from a single theoretical perspective.

Further questions and future work

There are three limitations to the current work. First is the question of generalisability from the experimental tasks. I investigated transfer in the letter sequence extrapolation domain, where different sequences and patterns served as proxy for different "contexts" as defined by their similarities and differences in surface features and pattern structures (for a similar micro-world approach to understanding analogy see Mitchell, 1993, and Hofstadter & FARG, 1995). Using a micro-world domain worked very well for a laboratory investigation of transfer because it provided excellent experimental control. Although these results provide a critical first step to investigating and understanding the interactions of these mechanisms, this work needs to be extended to more real-world transfer topics (e.g., learning statistics, Fong & Nisbett, 1991) and settings (e.g., classroom, De La Paz & Graham, 2002). In addition, these interactions need to be explored after longer time delays between learning and problem solving to test how robust

the application conditions are for each mechanism. A second limitation is that the learning component in this experiment was very brief. In Experiment 2 the learning session was only 1 ½ hours long. Therefore these findings apply to how novices perform learning and transfer tasks. How would a person's performance look after extensive training on the materials? Future work should look at the impact of expertise on the use of multiple mechanisms of transfer. Finally, although the current work provides a novel framework for conceptualising transfer as composed of multiple mechanisms with different application conditions, much of computational specifics of the theory remain to be worked out. Future work should develop a computational model that includes each mechanism as well as algorithms to specify how they interact given particular learning and problem-solving experiences.

A broader view

The results from this work suggest that in order to understand transfer, one must examine several interrelated aspects of the transfer scenario from multiple theoretical perspectives. More broadly, this work suggests that higher levels of analysis and synthesis are needed when investigating complex learning and problem-solving phenomena. That is, to understand complex cognitive processes such as knowledge transfer we need to understand the *interaction* of the basic cognitive mechanisms of the mind. This line of reasoning further suggests that progress in the cognitive sciences is dependent on the investigation of separate strands of cognitive phenomena, as well as work that integrates and synthesises across those strands by weaving more general theories.

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