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REGULAR ARTICLE

Categories of Illustrated Problems for Training Children in Inductive Reasoning

Melissa Lopez Reyes[1] · **Rajiv K. Amarnani**[1,2]

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Abstract Klauer and Phye's *Cognitive Training for Children* (Cognitive training for children: a developmental program of inductive reasoning and problem solving. Hogrefe & Hogrefe Publisher, Kirkland, 1994) provides instruction in inductive reasoning through a sequence of 120 illustrations following a prescribed two-way categorization (a) attributes of objects versus relations between objects, and (b) similarities or differences versus both similarities and differences in attributes or relations. While the program's effectivity has been established, its prescribed categorization of problems has yet to be validated. If training performance is in accordance with the prescribed categorization, then performance patterns should be more similar for problems in the same than in different categories. In the current research, correlations of performance between problem categories were used as similarity measures in multidimensional scaling. The resulting solution yielded the attribute–relation and similarity–difference dimensions thus showing that performance reflects problem complexity. Visual salience, however, may override problem complexity, as suggested by the finding that the matrix arrangement of objects facilitated training in the algorithmically complex similarity-and-difference problems. The use of everyday-life objects as opposed to abstract objects also was shown to facilitate inductive reasoning.

✉ Melissa Lopez Reyes
melissa.reyes@dlsu.edu.ph

Rajiv K. Amarnani
rajiv.amarnani@anu.edu.au

[1] Department of Psychology, De La Salle University, 2401 Taft Avenue, Manila 0922, Philippines

[2] Present Address: Research School of Management, The Australian National University, Canberra, Australian Capital Territory, Australia

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Introduction

Inductive reasoning is a dimension of mental ability that involves the extraction of patterns from observations to arrive at a generalization (Sternberg 1986). Although pattern detection presupposes a developed thinking process, children have been known to categorize objects according to less visually apparent dimensions (Gelman and Markman 1986). Children have also been known to employ adult-like reasoning so long as they work with familiar objects (Heit and Hahn 2001). Still, developing inductive reasoning happens over time as a product of maturation and everyday experiences (Kuhn and Franklin 2008). There is evidence, too, of stable improvement in children's inductive reasoning as a result of training, assistance, and exposure to appropriate materials (Tunteler et al. 2008; Tunteler and Resing 2007).

Klauer and Phye's *Cognitive Training for Children*

Separate from subject-matter learning and not included in standard school curricula is the programmed teaching of inductive reasoning, done with visual or textual materials that systematically show patterns of increasing complexity (Csapó 1997; de Koning et al. 2002; Hamers et al. 1998). Often, a prescribed structure is used during training that corresponds to the structure of the component skills (Christou and Papageorgiou 2007; Moseley et al. 2005). The component skills for inductive reasoning, as theorized by Klauer and Phye (1994), follow a similarity-based approach known to be practiced by children (Fisher 2005).

Specifically, Klauer and Phye (1994) follow a two-way categorization of problem complexity: (a) problems either require detecting simpler patterns in attributes of objects or more complex patterns in relations among objects (the attribute–relation categorization), and (b) problems either require detecting simpler patterns of similarity or of difference or more complex patterns of both similarity and difference (the similarity–difference categorization). With this categorization of problem complexity, Klauer and Phye (1994) designed *Cognitive Training for Children* (CTC) for the preschool and the early grades. An individualized or small-group training program, CTC consists of ten lessons in detecting patterns in illustrated objects (12 per lesson; a total of 120 illustrations).

The six problem categories arising from the two-way categorization are:

1. *Attribute/similarity* (*generalization*) problems require recognizing common attribute/s. They require grouping similar objects, or choosing the object that goes with a group, or identifying the common attribute. For example, a kite, a butterfly, and a helicopter are illustrated. The problem requires stating how these objects are similar.
2. *Attribute/difference* (*discrimination*) problems require recognizing the attribute/s that all objects, except one, share. For example, a telephone, a shovel, a watering can, and a hose are illustrated. The task is to determine which object is different from the rest.
3. *Attribute/similarity–difference* (*cross classification*) problems require recognizing both similarity and difference in a collection of objects, with objects either having or not having attribute A, as well as having or not having attribute B. Task variations include choosing from options the object that should go with a group of objects, or choosing in what group should a given object go, or, given a 2 × 2 matrix of objects, choosing from options which should go to a missing cell.
   For example, the following compartments of animals are illustrated: two hens and a rooster (birds, raised on a farm), a caged owl (bird, not raised on a farm), a pig (not a bird, raised on a farm), two caged bears (not a bird, not raised on a farm), and fish in an aquarium (not a bird, not raised on a farm). The rabbits, the animals that need to be classified, should go with the pigs.
4. *Relation/similarity* (*recognizing relations*) problems require recognizing how objects are similarly related. Problems require either completing or arranging a series, or completing an analogy. For example, on the first row of an illustration is shown a circle and a figure 8; on the second row is a figure D. The task is to choose from four objects (c, S, B, and P) the missing object on the second row.
5. *Relation/difference* (*differentiating relations*) problems require recognizing how some objects are related in a different way from how other objects are related. Problems require either spotting errors in a series, rearranging the series, or removing an odd object. For example, the following objects are illustrated from left to right: triangle, square, hexagon, five-sided polygon, and seven-sided polygon. The task is to spot the error in the series.
6. *Relation/similarity–difference* (*system construction*) problems require recognizing in a 2 × 2 matrix how objects are related in one way along the rows and in a different way along the columns. The task is to choose from four options the object to be placed in the missing cell in the second row and second column, such that the second row and second column follow the relations in the first row and first column, respectively.
   For example, the first row of an illustration contains a butterfly with one dot on the top right wing followed by a butterfly with one dot each on the top left and top right wings (row relation is "add a dot on the top left wing"). On the other hand, the first column contains the butterfly with one dot on the top right wing followed by a butterfly with two dots on the top right wing (column relation is "add a dot on the top right wing"). To complete the matrix, the butterfly to place in the second row/second column should be a butterfly with a dot on top left wing (row relation: add a top on the left top wing, where initially there is none) and with two dots on the top right wing (column relation: add a dot on the top right wing, where initially there already is one).

Problems also vary according to whether objects are *blocks* (of various shapes and colors), *everyday-life objects* (e.g., butterflies, shoes), *everyday-life scenes* (e.g., houses on a street, a boy who has fallen from a ladder), or *letters/configurations* (i.e., configurations of lines and dots).

The focus of research on instructional programs lies firstly in establishing transfer-of-learning effects (Perkins and Salomon 1992) and, indeed, most research done on the CTC addresses this issue. The finding that learning "transfers" to other tasks that tap inductive processes but not to tasks that do not tap inductive processes indicates that CTC builds inductive reasoning and not just some general cognitive skill (Klauer et al. 2002; Klauer and Phye 2008). Furthermore, effects have been shown to be more than just practice effects since transfer happens even with dissimilar (but still inductive) tasks (Roth-van der Werf et al. 2002) and persists over time (Klauer and Phye 2008; Molnár 2011; Tomic and Klauer 1996).

Findings of transfer effects are documented in Hager and Hasselhorn's (1998) meta-evaluation of studies comparing participants trained with CTC with control or alternative-treatment participants on various cognitive

measures. The meta-evaluation shows that CTC leads to improved performance in tests of fluid intelligence, has better outcomes than the no-treatment condition, and is at least comparable with competing cognitive training programs. Improved performances in the Raven's Colored Progressive Matrices and in the Culture Fair Test from pretest to posttest and from posttest to follow-up are the evidence of transfer durability.

Validating the Two-Way Categorization

Although extant studies have established CTC's effectiveness, the two-way problem categorization around which the program has been designed has not yet been validated against training performance data. Such validation would be of interest, because of Hager and Hasselhorn's (1998) attribution of the program's effectiveness to the design of the problems rather than to the strategies taught during training. Klauer (1985) indeed has mentioned the importance of empirically validating the problem categories over and above rational analyses.

It is the aim of this study to determine whether CTC training performance reflects the prescribed categories. It is assumed that if performance patterns are more similar for problems in the same category than in different categories, then training performance actually reflects the prescribed categorization (cf. Watters and English 1995). Correlations of training performance between problem categories are used as similarity measures in multidimensional scaling (MDS; cf. Jaworska and Chupetlovska-Anastasova 2009). If training performance patterns are in accord with the prescribed problem categorization, then we expect to see in the two-dimensional MDS solution the attribute–relation and similarity–difference dimensions.

Another aim of this study is to validate through MDS the distinction between illustrations of everyday-life and of abstract objects. The finding that decontextualized, abstract content contributes to problem complexity and requires sophisticated reasoning (Handley et al. 2004), and the finding that the greater visual salience of the so-called sociocognitive items (i.e., everyday-life) facilitates performance (Roberts et al. 2000), both suggest different performance patterns for everyday-life and abstract objects.

Another matter to be considered in the validation is that CTC is a training program and not an assessment instrument and thus the influence of instruction needs to be accounted for. Disentangling instructed from uninstructed problem solving is important, because instruction actually is known to prompt children to take on a formal, logical approach to problem solving (Leevers and Harris 1999). Thus, two performance indicators, proposed by Klauer and Phye (1994), are used in this study: the percentage of problems solved without help, which indicates correct, unassisted problem solution; and, the percentage of problems not solved despite help, which indicates the limit of adult assistance in facilitating problem solution.

To summarize, training performance in the CTC is used to validate the distinction between (a) problems involving attributes versus relations, (b) problems involving similarity or difference-only versus both similarity and difference, and (c) problems involving everyday-life versus abstract objects. The correlation of the performance between two categories is taken as the measure of similarity between categories. These correlations are subjected to MDS to determine whether the dimensions of the MDS solutions correspond to the prescribed categorization.

Method

Participants

Participants were Filipino preschoolers of the College of Education of De La Salle University, Manila, Philippines. The college's preschool provides low-cost education to children in neighboring urban lower-income communities. There were six males and four females. There were four 4-year-olds (three males and one female); three 5-year-olds (one male and two females); two 6-year-olds (two males); and one 7-year-old (female). The first language of all participants is Filipino.

Materials

CTC has 120 problems of different combinations of problem category and illustration type. There are 20 problems for each of the six categories. There are 30 problems using blocks, 30 problems using everyday-life objects, 42 problems using everyday-life scenes, and 18 problems using letters/configuration. Shown in Table 1 are the number of problems for each combination of problem category and illustration type.

CTC was used with the English questions translated to Filipino.

Procedures

The trainers were three upperclass college students majoring in education. They were instructed by the first author on the training structure, problem categories, and training guidelines described in the manual.

Each preschooler-participant was trained individually by the same trainer throughout the program. Two trainers taught three preschoolers each and the third trainer taught four preschoolers. The trainers were in consultation with each other to ensure uniform program implementation.

Table 1 Number of problem categories per illustration type in Klauer and Phye's (1994) cognitive training for children

Problem category	Blocks	Everyday-life objects	Everyday-life scenes	Letters/ configurations	Total
Attribute/similarity	5	5	7	3	20
Attribute/difference	5	5	7	3	20
Attribute/similarity–difference	5	5	7	3	20
Relation/similarity	5	5	7	3	20
Relation/difference	5	5	7	3	20
Relation/similarity–difference	5	5	7	3	20
Total	30	30	42	18	120

Lessons were given daily or every other day as permitted by the school's schedule. No specific time allotment was given for each problem so that the lesson proceeded at the preschooler's pace. Each lesson was finished in less than an hour.

Training followed the order of problem presentation indicated in the manual with the 120 problems divided evenly into 10 lessons. The problems were sequenced so that there was progression from simpler to complex problems, as follows: training started with similarity-only problems, followed by difference-only, and then followed by similarity-and-difference. Blocks and everyday-life objects were introduced at Lesson 1 then removed at Lesson 7; everyday-life scenes were introduced at Lesson 3 then removed at Lesson 9; and, letters/configurations were used in Lessons 9 and 10. Attribute/similarity problems first appeared in Lesson 1, attribute/difference in Lesson 3, and attribute/similarity–difference in Lesson 5. Relation/similarity problems first appeared in Lesson 1, relation/difference in Lesson 4, and relation/similarity–difference in Lesson 7.

For each problem, the trainer showed the illustration and read the question. The child first worked independently. If the child solved the problem right, he or she was asked to explain the solution. The trainer elaborated on the solution, pointing out the pertinent similarity or difference in attribute or relation. If the child did not solve the problem right, help was extended in various ways as appropriate, such as describing the configuration of objects or asking questions about it, verifying if the child understood the question and rephrasing it as necessary, or asking the child how the objects were similar or different. For each problem, the trainer noted whether the problem was solved independently, solved with help, or not solved despite help.

MDS Analysis

The solution or output of MDS is the locations of given elements (e.g., car makes, cities) in a one-dimensional space (line), in a two-dimensional space (plane), or in some higher dimensional space. The exact locations of the elements are given by coordinates of points (e.g., by a number given a one-dimensional space, or by an ordered pair given a two-dimensional space). In MDS, the data used to compute the coordinates are the matrix of observed similarities between pairs of elements. Coordinates are derived in such a way that they result in the closest possible match between the distances of elements in the solution and the data of observed similarities (Diekhoff 1992; Johnson and Wichern 1992). When the coordinates are plotted, the visual depiction of the elements' relative positions shows in what respect, that is, along what dimensions, the elements differ from each other (Diekhoff 1992).

In this research, the elements examined in MDS are the problem categories. MDS also was conducted with illustration types as elements. The similarity between each pair of elements is the correlation of training performance between them. Thus, the greater the correlation of performance between elements, the more similar are the elements. As there are two measures of performance (problems solved without help, problems not solved despite help), separate MDS was conducted for each measure. The PROXSCAL, or proximity scaling, module of the Statistical Package for the Social Sciences (SPSS®) was used in conducting the MDS. A maximum number of 100 iterations was allowed, but this limit was not reached in any of the MDS conducted.

Results

MDS of Problem Categories

Shown in Table 2 are the correlations of training performance between problem categories. The lower diagonal (for problems solved without help) and the upper diagonal (for problems not solved despite help) were used in separate MDS.

Problems Solved Without Help

Shown in Fig. 1 are the locations of the categories as specified in the two-dimensional MDS solution. The

Table 2 Intercorrelations of training performance between problem categories: percentage of problems solved without help (lower diagonal) and percentage of problems not solved despite help (upper diagonal)

Problem category	1	2	3	4	5	6
1. Attribute/similarity	–	.45	.40	.26	−.21	.04
2. Attribute/difference	.74*	–	.46	.55	−.12	.12
3. Attribute/similarity–difference	.27	.35	–	.26	.23	.14
4. Relation/similarity	.74*	.67*	.03	–	.20	.44
5. Relation/difference	.59	.56	.26	.65*	–	.58
6. Relation/similarity–difference	.41	.41	.77*	.25	.23	–

* $p < .05$

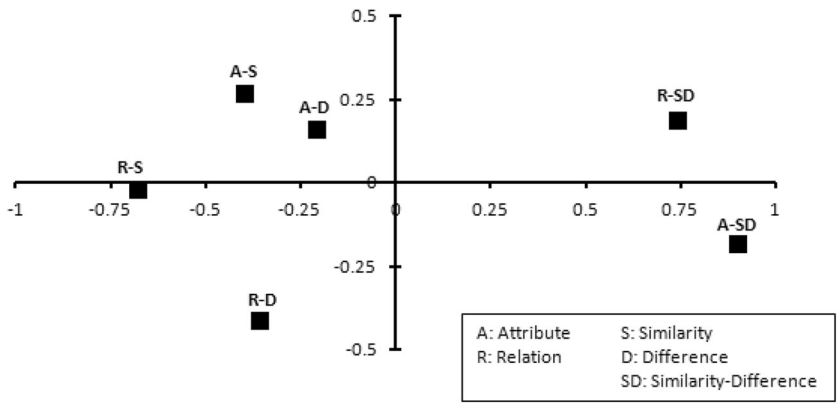

Fig. 1 Multidimensional-scaling solution of problem categories: problems solved without help

locations of points correspond closely to the similarity measures as indicated by adequate fit indices: a low normalized raw stress of .01, or a high Tucker's coefficient of congruence of .99 (Kruskal 1964).

The *x*-axis reflects the distinction among similarity, difference, and similarity-and-difference: similarity problems (coordinates −.68 and −.40) are followed closely by difference problems (coordinates −.36 and −.21). Further away and on the positive end are the similarity-and-difference problems (coordinates .74 and .90).

The *y*-axis partially reflects the attribute–relation distinction. Given similarity-only, relation problems have a lower coordinate (−.02) than attribute problems (.27). Likewise, given difference-only, relation problems have a lower coordinate (−.41) than attribute problems (.16). The pattern is reversed, however, given similarity-and-difference, where relation problems have a higher coordinate (.19) than attribute problems (−.18).

Problems Not Solved Despite Help

Shown in Fig. 2 are the locations of the six categories as specified in the two-dimensional MDS solution. The fit indices are adequate: the normalized raw stress is .01; the Tucker's coefficient of congruence is .99.

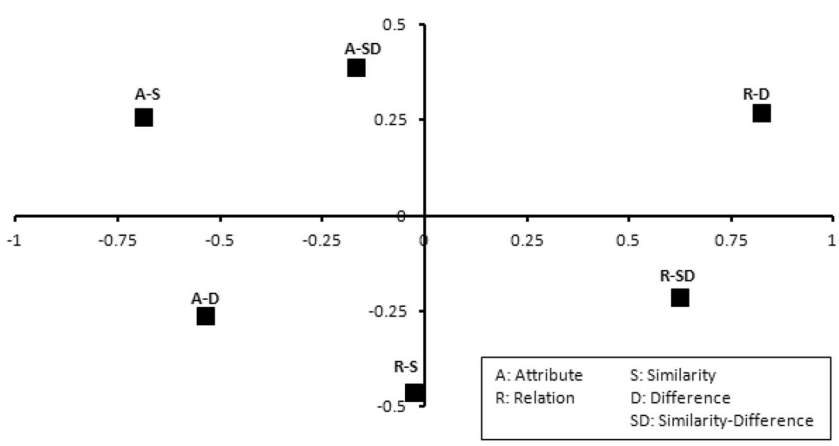

Fig. 2 Multidimensional-scaling solution of problem categories: problems not solved despite help

The *x*-axis reflects the attribute–relation distinction: attribute problems are closer to each other (with coordinates: −.69, −.54, −.17) and relation problems are closer to each other (with coordinates −.03, .62, .82).

The *y*-axis does not clearly reflect the similarity–difference distinction. On the negative side is a similarity → difference → similarity–difference ordering from bottom to top (with coordinates −.46, −.26, and −.21, respectively), albeit of different attribute–relation categories. There is also a similar ordering on the positive side (with coordinates .26, .27, .39), again of different attribute–relation categories.

MDS of Illustration Types

Shown in Table 3 are the correlations of training performance between illustration types. These correlations were used as similarity measures. The lower diagonal (for problems solved without help) and the upper diagonal (for problems not solved despite help) were used in separate MDS.

Problems Solved Without Help

Shown in Fig. 1 are the locations of the four illustration types as specified in the two-dimensional MDS solution. The fit indices are adequate: the normalized raw stress is .01; the Tucker's coefficient of congruence is .99.

The *x*-axis reflects a complexity-of-arrangement dimension: the simpler arrangements of everyday-life objects and blocks have positive loadings (with coordinates .52 and .58, respectively), while the more complex arrangements of everyday-life scenes and letters/configurations have negative loadings (both with coordinate −.55).

The *y*-axis reflects an everyday-life versus abstract objects dimension: everyday-life objects and scenes have positive loadings (with coordinates .34 and .15, respectively), while blocks and letters/configurations have negative loadings (with coordinates −.32 and −.17, respectively).

Table 3 Intercorrelations of training performance between illustration types: percentage of problems solved without help (lower diagonal) and percentage of problems not solved despite help (upper diagonal)

Illustration type	1	2	3	4
1. Blocks	–	.36	.66*	.63
2. Everyday-life objects	.64*	–	.12	.42
3. Everyday-life scenes	.52	.52	–	.62
4. Letters/configurations	.51	.53	.72*	–

* $p < .05$

Problems Not Solved Despite Help

Shown in Fig. 2 are the locations of the four illustration types as specified in the two-dimensional MDS solution. The fit indices are adequate: the normalized raw stress is .01; the Tucker's coefficient of congruence is .99.

Neither the *x*- nor the *y*-axis corresponds to everyday-life versus abstract and simple versus complex dimensions. The solution, however, suggests a separation between simple and complex arrangements: on opposite ends of the *x*-axis are the simpler everyday-life objects (.88) and the more complex everyday-life scenes (−.53), which have a much smaller difference in their *y*-axis coordinates; and, on the opposite ends of *y*-axis are the simpler blocks (−.32) and the more complex letters/configurations (.50), which have a much smaller difference in their *x*-axis coordinates (Figs. 3, 4).

Discussion

CTC trains younger children in detecting patterns of similarities or differences in either attributes of, or relations among, illustrated objects. Thus, CTC is founded on the

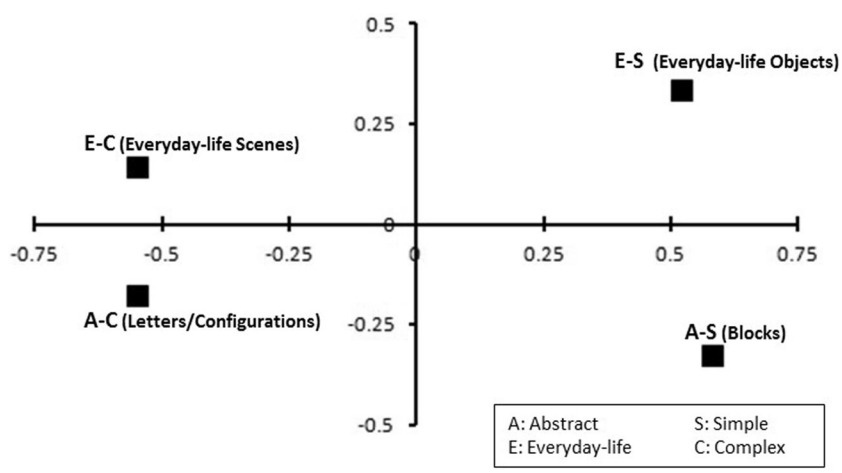

Fig. 3 Multidimensional-scaling solution of illustration types: problems solved without help

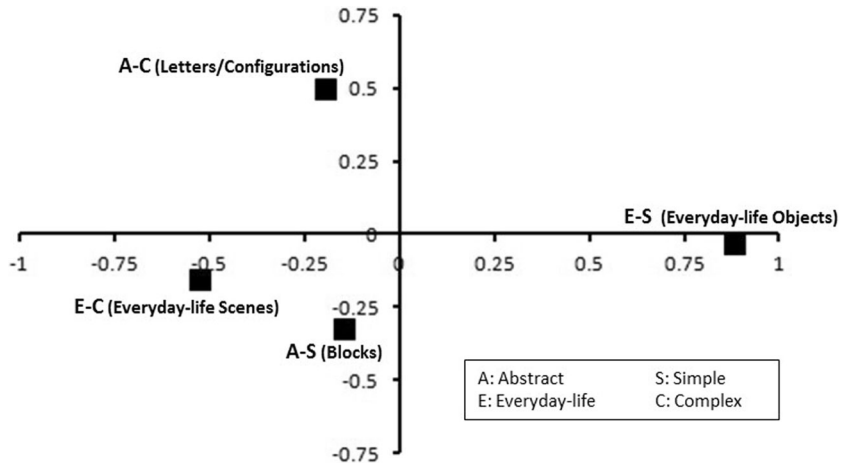

Fig. 4 Multidimensional-scaling solution of illustration types: problems not solved despite help

two-way categorization of similarity–difference and attribute–relation. The current research validated this categorization against training performance by examining whether problems of the same or similar categories are located closely to each other in the MDS space. The MDS approach used in this study is in keeping with its utilization in measurement research, where the objective is to categorize constructs (e.g., personality, emotions) and to examine their similarity with each other (Jaworska and Chupetlovska-Anastasova 2009). In this study, the MDS conducted on training performance shows how CTC's problems adhere to the similarity–difference and attribute–relation dimensions. Furthermore, the MDS on illustration types shows the a priori distinction of everyday-life versus abstract objects, as well as a distinction between simple and complex arrangements.

The Issue of Sample Size

The MDS conducted rests on different sample sizes: six problem categories were mapped in MDS space, as were four illustration types. The correlation used as similarity measure between problem categories (or between illustration types) was computed from an n of 10 preschoolers. The score on a problem category was based on 20 problems. The score on an illustration type was based on 30 problems for blocks and everyday-life objects, 42 for everyday-life objects, and 18 for letters/configurations (refer to Table 1 for the number of problem categories per illustration type.)

The sample size limitation of this study is neither in the number of elements subjected to MDS (Jaworska and Chupetlovska-Anastasova 2009) nor in the number of problems used to arrive at training scores, but only in the number of preschoolers.

This sample size is lower, but not markedly so, than the training-group sample sizes in the studies analyzed by Hager and Hasselhorn (1998). Fourteen of these studies trained children either individually or in pairs. In these studies, the number of children trained using CTC ranges from 8 through 72. Three studies have larger sample sizes (25, 30, 72), while the remaining sample sizes range from 8 to 16. The median sample size is 14.5. In this study, the limitation posed by small sample size on the stability of similarity measures warrants replications. Nevertheless, the MDS results reveal a systematic pattern of correspondences between the similarity measures of training data and the prescribed two-way categorization.

Certainly, however, the small number of participants in this study poses a limitation in determining performance differences across sex and age (ranging from 4 to 7). As ancillary analyses, a series of one-way analyses of variance (ANOVAs) was run with sex as the independent variable and the following as dependent variables: percentages of problems solved without help across the six problem categories and across the four illustration types; and, percentages of problems not solved despite help across problem categories and across illustration types (see "Appendix 1" for the table of means). Analogous analyses were run with age as the independent variable (see "Appendix 2" for the table of means). We note that it was not possible to examine age × sex interaction effects given that there was only one 7-year-old male participant.

Due to the small number of participants, majority of these analyses has low power. There is, however, a significant sex difference on the percentage of attribute–difference problems solved without help, $F(1, 8) = 5.44$, MSE = 223.44, $p = .05$, with boys solving more problems than girls. Boys also solved significantly more problems with everyday-life objects than did girls, $F(1, 8) = 5.94$, MSE = 116.09, $p = .05$. Lastly, there is a significant effect of age on the percentage of attribute–difference problems solved without help, $F(3, 6) = 10.87$, MSE = 77.78, $p = .01$. Post hoc Tukey tests show that 6-year-olds performed better than did the other age groups.

The Similarity–Difference and Attribute–Relation Dimensions

The MDS solution for problems solved without help yielded a similarity–difference dimension: the similarity-only and difference-only problems load low on this dimension, while the more complex similarity-and-difference problems load high. At the outset, this dimension can be taken to mean that detecting both a similarity and a difference in the same illustration of objects is more algorithmically complex than detecting a similarity-only or a difference-only.

Ancillary analysis using repeated-measures ANOVA, however, shows a significant similarity–difference × attribute–relation interaction effect, $F(2, 18) = 12.61$, $\mathrm{MSE} = 73.47$, $p = .00$, $\varepsilon^2 = .58$. Shown in the top panel of Table 4 are the mean percentages of problems solved without help for the different factorial combinations of attribute–relation and similarity–difference.

Post hoc Tukey's honestly significant difference (HSD) tests reveal the nature of this interaction. Given attributes, similarity-and-difference problems are not any more difficult than the similarity-only and difference-only problems. On the other hand, given relations, similarity-and-difference problems are in fact easier than similarity-only, although just as easy as difference-only.

When the ancillary analysis is done on the percentage of problems not solved despite help, similarity–difference × attribute–relation interaction effect is also significant, $F(2, 18) = 4.98$, $\mathrm{MSE} = 95.97$, $p = .00$, $\varepsilon^2 = .36$. Shown in the bottom panel of Table 4 are the mean percentages of problems not solved despite help.

Post hoc Tukey's HSD tests show that the patterns of mean differences in percentage of problem not solved despite help are largely the same as those of the above-mentioned mean differences in percentage of problems solved without help. Given attributes, similarity-and-difference problems are not any more difficult than the similarity-only and difference-only problems. On the other hand, given relations, similarity-and-difference problems are in fact easier than similarity-only and difference-only.

A possible explanation of how children are able to reason out similarity-and-difference problems is given by Hager and Hasselhorn's (1998) perception hypothesis, which attributes the CTC's transfer effects not solely to enhanced inductive reasoning but to enhanced perceptual efficiency. In their meta-evaluation of studies that examined the program's transfer effects, Hager and Hasselhorn (1998) point out a number of results that support the perception hypothesis. First, the program's positive transfer on the Raven's Coloured Progressive Matrices (Raven et al. 1995) cannot be singularly attributed to enhanced inductive reasoning, because the Raven's taps both inductive reasoning and visual–perceptual ability. Second, across the different subtests of the Culture Fair Test for younger children (Cattell 1963; Cattell and Horn 1978), the program's pretest–posttest gains were larger for subtests that tap perceptual and psychomotor abilities than for subtests that tap inductive reasoning. Third, the program's positive transfer on the Developmental Test of Visual Perception was comparable to, and not smaller than, that of the Frostig Developmental Program of Visual Perception (Frostig et al. 1961; Maslow et al. 1964). Hager and Hasselhorn's (1998) conclusion is that the training provided by the CTC develops not so much from the ability to reason out rules for extracting patterns as from the ability to extract patterns through visual perception.

We adapt the perception hypothesis to argue that, in the MDS solution, similarity-and-difference problems are set apart from similarity-only and difference-only problems not because the former problems require a distinct inductive algorithm but because the objects in the similarity-and-difference problems are presented in a 2 × 2 matrix much oftener than are the similarity-only and difference-only problems. Seven of the 20 attribute/similarity–difference problems and 10 of the 20 relation/similarity–difference problems are in matrix form. In contrast, the other problem

Table 4 Means (and standard deviations) of percentage of problems solved without help and percentage of problems not solved despite help for the factorial combinations of attribute–relation and similarity–difference

Similarity–difference	Attribute		Relation	
	M	SD	M	SD
Problems solved without help				
Similarity	48.5	14.2	18.0	9.8
Difference	38.5	18.3	29.0	11.5
Similarity–difference	36.5	20.3	31.5	17.2
Problems not solved despite help				
Similarity	14.0	9.7	34.5	13.2
Difference	26.5	10.0	36.0	14.9
Similarity–difference	20.0	11.6	21.0	10.2

categories are not presented in matrix form except 4 of the 20 relation/similarity problems.

A matrix arrangement actually makes attributes and relations more visually noticeable and, consequently, more easily solved (Gentner and Medina 1998). Thus, the matrix arrangement makes similarity-and-difference problems easier, or at least as easy, as the less algorithmically complex but non-matrix type similarity-only and difference-only problems.

Interestingly, the facilitation of visual–perceptual processing brought about by the matrix arrangement is greater with relation than with attribute problems; this is suggested by the finding that similarity-and-difference *relation* problems are easier than similarity-only and difference-only *relation* problems (but given attributes, these problems have comparable difficulty). That induced visual–perceptual efficiency facilitates inductive reasoning in the more difficult relation problems is supported by Watters and English's (1995) study showing that inductive reasoning with drawings is more highly correlated with performance in simultaneous, spatial processing (Matrix Tests and Raven's Colored Progressive Matrices) than in performance in successive, rule-based processing (number span, word string, and letter span tests). Spatial abilities have also been shown to predict elementary school children's performance in scientific reasoning (Mayer et al. 2014).

Relation problems, in fact, have been shown to be distinct from attribute problems in the MDS solution for problems not solved despite help. The difference between relation and attribute problems is likely a difference in complexity, as suggested by the result, from ancillary analyses using repeated-measures ANOVAs, that fewer relation than attribute problems were solved without help, $F(1, 9) = 33.75$, $\mathrm{MSE} = 100.00$, $p = .00$, $\varepsilon^2 = .79$; the mean percentages of solved problems are 26.2 (SD = 14.1) and 41.27 (SD = 17.9), respectively, for relation and attribute problems. Likewise, more relation than attribute problems were not solved despite help, $F(1, 9) = 8.41$, $\mathrm{MSE} = 190.50$, $p = .00$, $\varepsilon^2 = .48$; the mean percentages of unsolved problems are 30.5 (SD = 14.2) and 20.2 (SD = 11.3), respectively, for relation and attribute problems.

The Everyday-Life Versus Abstract and Simple Versus Complex Dimensions

The MDS solution for problems solved without help shows a distinction between everyday-life objects (everyday-life objects, everyday-life scenes) and abstract objects (blocks, letters/configurations of lines and dots); and, a distinction between simple (everyday-life objects, blocks) and complex arrangements (everyday-life scenes, letters/configurations). The simple–complex dimension is also reflected in the MDS solution for problems not solved despite help.

Although the everyday-life versus abstract dimension is prescribed by Klauer and Phye (1994), there is no prescribed explanation why the "everyday-ness" or ordinariness of materials would facilitate inductive reasoning. Transfer-of-learning literature, however, indicates that the transferability of inductive reasoning may be delimited by task material (e.g., Tomic and Klauer 1996). Also, participants are known to bring about their background knowledge of the materials when reasoning inductively (Heit and Rubinstein 1994). There, too, is evidence that children readily consider familiar thematic relations so that highlighting these themes would facilitate diversity-based reasoning (Heit and Hahn 2001). Finally, the materials' "everyday-ness" or ordinariness is more readily visually processed, given children's familiarity with them (Roberts et al. 2000). Together, these results suggest that using everyday-life objects facilitates inductive reasoning.

Another dimension to be reckoned with is the simple–complex dimension of the MDS solutions. A complex arrangement contains more external irrelevant details that must be ignored in order to notice internal relations. We can thus reason that complexity of object arrangement is yet another aspect that inhibits visual–perceptual processing, but ancillary analysis with ANOVA does not indicate so: problems with complex and simple arrangements are comparable in the percentage of problems solved without help and not solved despite help. The most that can be concluded from the MDS solution is that simple and complex arrangements are processed differently but with comparable levels of competence.

Visual–Perceptual and Inductive-Reasoning Skills

Through trainers' one-on-one interaction with children, verbal instruction becomes a medium for training, with precise descriptions of similarities and differences in attribute or relation being a key to training success. This research shows that aside from verbal-instruction scaffolding, perceptual-processing scaffolding would facilitate inductive reasoning. Specifically, perceptual-processing scaffolding is afforded when patterns of relations are organized using a matrix arrangement and when familiar, everyday-life objects are used.

The importance of visual–perceptual processing of illustrations in inductive-reasoning problems extends to other forms of cognitive tasks and training. Under certain circumstances, perceptual similarity has been shown to facilitate children's ability for analogical reasoning and for associating a model to its referent (DeLoache and Sharon 2005). Feuerstain's cognitive development program (Ben-

Hur and Feuerstein 2011) provides a visual–spatial orientation module that trains children to use verbal labels and to describe spatial orientation. Relatedly, spatial–imaginal and verbal–propositional have been identified as two of five environment-oriented cognitive systems (Demetriou and Kyriakides 2006).

The current research shows that CTC's effectiveness lies, in part, on the way perceptual-processing scaffolding supports verbal-instruction on inductive reasoning. Klauer and Phye (1994) proposed two such strategies: the analytic strategy of comparing objects and systematically finding out the similarity and difference; and, the heuristic strategy of starting with a more global inspection, and proposing and then confirming or disconfirming the hypothesis. In both strategies, perceptual-processing scaffolding will be of aid. Matrix problems make salient the similar and different attribute or relation and the systematic inspection required in the analytic strategy can more readily commence. The global-inspection strategy is helped, too, by visual–perceptual scaffolding: the matrix format orders objects according to their similarities and differences, thus, highlighting patterns and deemphasizing irrelevancies.

This study draws attention to the possibility that CTC may develop perceptual processing in addition to inductive reasoning. While there is reason to believe that perceptual processing facilitates inductive reasoning (Hager and Hasselhorn 1998), these are classically viewed as distinct cognitive processes (McGrew and Wendling 2010), with perceptual processing loading under visual processing (*gv*) and inductive reasoning loading under fluid intelligance (*gf*) in the Cattell–Horn–Carrol framework of cognitive ability (McGrew 2005). Further research may determine whether CTC develops other constituent cognitive processes, such as working memory capacity (*Gsm*), and perceptual speed (*Gs*), and whether any observed effects of CTC on these processes are responsible for the observed positive effects of CTC on test performance and academic achievement (Klauer and Phye 1994). Examining these constituent cognitive processes may further unpack the benefits of CTC, as well disentangle the mechanisms by which children develop inductive reasoning.

In summary, this research has shown support for the prescribed problem categorization of the CTC, while providing support for the burgeoning proposition that visual–perceptual processing is crucial for inductive reasoning with illustrations of objects—and that the CTC taps this form of processing as well. While these findings highlight the importance of visual–perceptual competence in solving inductive-reasoning problems, it does not singularly account for the pattern of inductive reasoning observed in our sample. Inductive strategy itself still plays a critical role; this is apparent in the observed similarity–difference and attribute–relation dimensions.

Both inductive and visual–perceptual processes deserve attention in studying CTC's transfer effects. To what extent do acquired inductive-reasoning strategies and visual–perceptual competence contribute to transfer? At the outset, inductive-reasoning strategies alone should mediate the transfer effects; yet it is certainly possible that the visual–perceptual competence gained through training also contributes to performance. For example, perceptual efficiency may explain transfer to fluid-intelligence tests through its contributions to working memory (Woodman et al. 2003). Identifying transfer mechanisms is the next step in understanding how training works and in developing targeted interventions.

Cognitive Training in Larger Contexts

Although the current research has focused only on one particular training program, its approach in validating the structure and categories of training problems can be applied to other inductive-reasoning training programs and even to programs designed to develop other structured or logical forms of thinking. With such programs, articulating the structure and categories of tasks has been a *sine qua non*. For example, de Koning et al. (2002) present a structure of an inductive-reasoning training program that draws from Klauer's work, but is different from the CTC, and in Feuerstein's programs (Ben-Hur and Feuerstein 2011), the logical, developmental organization of training remains to be a primary concern. Frameworks and taxonomies continue to be designed for components of thinking, or for thinking in general (e.g., Moseley et al. 2005). The current research presents an approach to validating prescribed structures of training programs.

Notwithstanding this study's small sample size, the meaningful problem categorization resulting from the MDS presents the possibility that these results can be replicated not only with larger sample sizes but, more importantly, with other training conditions and populations of students. Variations of the CTC have been documented, for example, the use of small-group instead of individual training (Barkl et al. 2012) and the use of other objects, pictures, and materials (Molnár 2011). Interestingly, the CTC has already taken on a somewhat international stature, as it has been studied with students from varied cultures, largely in Germany (Klauer and Phye 2008; Klauer et al. 2002), but also in Australia (Barkl et al. 2012), the Netherlands (Hamers et al. 1998; Roth-van der Werf et al. 2002), and in the case of the current research, the Philippines. It would thus be of interest to determine if the validated two-way problem categorization of the CTC, including the observed influence of visual salience during training, is invariant across training conditions and populations of students.

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Appendix 1

Mean percentages of problems solved without help and of problems not solved despite help for boys and girls across problem categories and illustration types (with standard deviation)

Problems	Solved without help		Not solved despite help	
	Boys	Girls	Boys	Girls
Problem categories				
Attribute/similarity	55.0 (13.4)	38.8 (9.5)	14.2 (11.1)	13.8 (8.5)
Attribute/difference	47.5 (16.4)	25.0 (12.3)	25.8 (11.6)	27.5 (8.7)
Attribute/similarity–difference	40.0 (23.0)	31.3 (17.0)	18.3 (13.3)	22.5 (9.6)
Relation/similarity	22.5 (10.4)	11.3 (2.5)	28.3 (12.5)	43.8 (8.5)
Relation/difference	32.5 (12.9)	23.8 (7.5)	30.0 (12.7)	45.0 (14.7)
Relation/similarity–difference	31.7 (16.3)	31.3 (21.0)	20.0 (10.0)	22.5 (11.9)
Illustration types				
Blocks	41.7 (9.6)	26.7 (13.1)	24.4 (8.3)	33.3 (5.4)
Everyday-life objects	39.4 (11.0)	22.5 (10.3)	22.2 (5.0)	30.0 (12.8)
Everyday-life scenes	36.1 (12.9)	31.0 (8.3)	20.6 (10.0)	22.0 (8.1)
Letters/configurations	35.2 (23.2)	25.0 (19.5)	25.9 (13.0)	37.5 (5.3)

Appendix 2

Mean percentages of problems solved without help and of problems not solved despite help for the different ages across problem categories and illustration types (with standard deviation)

Problems	Solved without help				Not solved despite help			
	Four	Five	Six	Seven	Four	Five	Six	Seven
Problem categories								
Attribute/similarity	45.0 (18.7)	45.0 (0.0)	65.0 (7.07)	40.0	20.0 (13.0)	10.0 (5.0)	7.5 (3.5)	15.0
Attribute/differences	40.0 (10.8)	28.3 (7.6)	65.0 (0.0)	10.0	23.8 (14.4)	33.3 (2.9)	20.0 (0.0)	30.0
Attribute/similarity–difference	23.8 (9.5)	48.3 (30.6)	50.0 (0.0)	25.0	21.3 (12.5)	16.7 (17.6)	20.0 (7.1)	25.0
Relation/similarity	22.5 (11.9)	11.7 (2.9)	22.5 (10.6)	10.0	31.3 (14.4)	45.0 (10.0)	25.0 (14.1)	35.0
Relation/difference	28.8 (14.4)	21.7 (7.6)	40.0 (7.1)	30.0	37.5 (15.0)	40.0 (21.8)	25.0 (7.1)	40.0
Relation/similarity–difference	23.8 (17.0)	36.7 (25.2)	40.0 (7.1)	30.0	25.0 (7.1)	25.0 (13.2)	10.0 (7.1)	15.0
Illustration types								
Blocks	33.3 (11.9)	38.9 (5.1)	48.3 (2.4)	10.0	29.2 (8.3)	31.1 (7.7)	18.3 (7.1)	33.3
Everyday-life objects	31.7 (11.7)	28.9 (13.5)	48.3 (7.1)	16.7	25.0 (7.9)	31.1 (13.9)	20.0 (.0)	20.0
Everyday-life scenes	31.5 (12.5)	28.6 (8.2)	47.6 (3.4)	33.3	23.2 (11.4)	21.4 (11.0)	16.7 (3.4)	21.4
Letters/configurations	22.2 (26.8)	33.3 (24.2)	41.7 (11.8)	38.9	31.9 (13.9)	35.2 (8.5)	16.7 (.0)	38.9

Standard deviation is not reported when $n = 1$

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