THE EFFECTS OF CONCEPT ACQUISITION COMPONENTS AI (ATTRIBUTE IDENTIFICATION) AND RL (RULE LEARNING) ON THE ACQUISITION AND TRANSFER OF COMPLEX CONCEPTS

by

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ABSTRACT

The present study considered a concept as the sum of two components: attributes and a rule. Extension of this model to the process of concept acquisition led to the notion of two component processes: attribute identification and rule learning. A subject provided with the relevant attributes in a task has only to acquire the correct conceptual rule. This process was called rule learning (RL). Initial provision of the appropriate rule requires only the acquisition of the relevant attributes, a process called attribute identification (AI). Provision of no initial information requires the learner to acquire both conceptual components. This process is called complete learning (CL).

Seventy-two subjects were divided into six training groups. Five of these groups were assigned to learning paradigms that provided training on two complex concepts under varying amounts of initial information (CL-CL; AI-AI; AI-RL; RL-AI; and RL-RL). The sixth group acted as a control and performed filler tasks in place of the training tasks.

The results showed that first-task learning in the paradigms had a significant effect on transfer performance. RL-first learners manifested the best transfer performance. An analysis of acquisition performance on the first learning task showed superior performance on the RL task followed by AI and CL tasks in that order.

Implications of these results to practical classroom activity were discussed and illustrated with the use of an example from science education.

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Dr. S. S. Blank, Thesis Committee Chairman

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I. Introduction:

Many recent studies considering variables related to concept acquisition tasks have considered concept acquisition to be a combination of two separable components, viz. attribute identification (AI) and rule learning (RL) (e.g., Haygood & Bourne, 1965; Lee & Gagne, 1970; and Lee, 1968). Others, such as Guthrie (1967) refer to these components as example learning and rule learning. Haygood & Bourne (1965) had subjects (Ss) engage in acquisition tasks under varying amounts of initial information. Those Ss in the AI condition were provided with the rule required to solve the acquisition task whereas Ss under the RL condition were provided with information on the specific relevant attributes. Hence, in each condition S was required to acquire the missing component of the concept before solution of the task could occur. Haygood & Bourne included a complete learning (CL) task in which Ss were provided with no information on either the rule component or the attribute component, barring the presentation of the name of the relevant and irrelevant dimensions that were included in the task. These same investigators found that in terms of errors to criterion, the CL task was the most difficult followed by the AI and RL tasks in that order. Guthrie (1967) used cryptograms and two types of rules (substitutional and transpositional) to investigate the effect of example learning (Example) and rule learning (Rule) on both retention and transfer. He found that the Example and Example-Rule groups surpassed the Rule-Example and the Control groups on the transfer task but not on the retention tasks.

More recently, Lee & Gagné (1970) investigated the effects of degree of learning of the component tasks on the acquisition of a complex conceptual rule. Their findings support a mediational interpretation of the cognitive integration of conceptual components in the acquisition process since overlearning and symmetrical learning of the two components was found to be more facilitative than a symmetrical learning or simple criterion learning of the components. The effect of over-learning of a concept on the relearning of the same concept has been studied by Ludvigson (1966). He found that with an interpolated series of confusion trials, overlearning facilitated the relearning of the original concept. Richardson (1956), using both different materials and a different technique, found that interpolated learning was not an effective variable on the retention of a concept. When these latter findings are considered in conjunction with the former results reported on the AI and RL acquisition components, interesting problems arise.

Purposes of study:

A general question arises regarding the effect of concept acquisition under varying amounts of initial information on transfer to a new complex concept. That is, do RL learners and AI learners perform equally well on a transfer task having been trained under these different conditions? One of the purposes of the present study is to determine not only if RL learners and AI learners perform differentially on a transfer task but if a combination of these learning methods produces superior transfer to, say, training under the CL method. That is, do learners who have training on a RL task followed by an AI task (RL-AI) perform significantly better on a transfer task than learners in the reverse sequence (AI-RL)? If the balanced or symmetric acquisition of the two components of a complex conceptual rule as considered by Lee and Gagné (1970) is extended to the two components AI and RL of concept acquisition itself, then this specific question arises: if the components of two concepts are learned relatively symmetrically (under learning paradigms AI-RL, RL-AI, and CL-CL), will performance on the transfer task be facilitated compared to learning or identification of the conceptual components under asymmetrical paradigms (i.e., AI-AI and RL-RL)?

On two training tasks, it would be reasonable to expect a within-group transfer effect. The magnitude and direction of such an effect as detected by the differences of response measures on the two tasks should assist in illuminating the dynamics of each training paradigm. Such an analysis would provide information relating to variations between group-specific strategies presumably employed by Ss on the training phase of the experiment. The different strategies available to Ss in different treatment conditions prior to attempting the transfer task are certainly of interest and pertinent to the total transfer effect as measured on the transfer task. A purpose of this study will therefore be to determine the effect of training as related to acquisition strategy and the relationship of acquisition strategy to concept transfer. An analysis of concept acquisition under the three acquisition paradigms (CL, AI, and RL) will be essential to testing the predictive theory relating to acquisition strategies and transfer.

Predictions and Hypotheses:

The total amount of information required by S to acquire a concept comes from two sources. First, on all component paradigms consisting of two tasks (i.e., AI-AI, AI-RL, RL-AI, and RL-RL), a definitive statement on one of the conceptual components is provided by the experimentor (E). Secondly, S can acquire the remaining necessary information for himself by considering the combined visual stimuli and verbal feedback from E. With regards to the information provided by E, the question must be asked whether S understands equally well a definition of a complex rule (be it verbal, written, or in Venn diagram form) under AI and a statement that certain attributes (e.g., shape and size) are important, under RL. The better performance under the RL paradigm reported by Haygood & Bourne could be explained by the greater ease of understanding the "given" component (viz. attributes) compared to understanding the "given" rule under the AI condition. With no attribute or rule information provided initially under the CL condition, it is readily understandable why this learning condition would be the most difficult.

It can be argued that the content of the given information is closely related to the strategies employed by S during acquisition. Since the transfer task is itself under the CL condition in this study, it would seem that similarity of instructions for the transfer task with those under the CL-CL training paradigm would cue S to continue using a strategy which would be most beneficial to acquisition on the transfer task. Further, it would seem that the dissimilarity in transfer task instructions for Ss under component paradigms would require a shift in strategies producing less efficient transfer and subsequent poorer performance on the CL transfer task. However, factors such as ease of acquisition on the training tasks, separation of conceptual components during training and distinction of these components must play a part in the development of an acquisition strategy. Perhaps too the symmetric acquisition of the components during training affects the acquisition strategy available to S as he begins the transfer task. Surely concept acquisition on the component paradigms would provide much greater separation and distinction of the conceptual components than would training under the CL method. This lack-of-component-separation effect for CL learners could very well outweigh the similarity-of-strategy effect. It is hypothesized that transfer performance and efficiency for Ss trained under the CL-CL paradigm will be substantially poorer than the transfer performance and efficiency observed for Ss trained under the component paradigms.

Similarly, a differential effect of training under mixed paradigms on transfer performance can be predicted. From the argument dealing with availability of information to S resulting from instructions on the AI and RL paradigms, it is hypothesized that Ss under the RL-AI condition will perform better on the transfer task than Ss under the AI-RL paradigm. Under the RL-AI sequence, the Ss will be provided with the attributes on task 1. According to the results of the Haygood & Bourne (1965) study, these Ss should have minimal difficulty acquiring the appropriate rule. Now, having just learned the complex rule, E will proceed to provide a clearly-worded definitive statement of this identical rule as part of the instructions for the second training task under the AI condition. (Training tasks 1 and 2 have identical rules.) Clearly, the liklihood of these Ss understanding the given rule having just learned it should be very good compared to Ss under the reversed sequence AI-RL. In the AI-RL condition, the rule is first provided on task 1. Understanding of the complex rule and application of that rule to the acquisition task will not be as efficient as understanding the attributes given on task 1 in the RL-AI sequence. Hence, some rule learning may take place in the AI task. If this is the case, the first AI task acquisition requirements are approaching the CL task requirements. Having come to criterion on task 1 in the AI-RL sequence, S is then provided with the easily-understood attributes and must arrive at the rule himself on task 2. For him, distinction and cognitive separation of the conceptual components at the end of the two training tasks is not nearly as complete as it is for Ss under the RL-AI paradigm. Hence, it is argued that the opportunity for S to develop a strategy that takes into consideration the two-component nature of the task at hand is not as great under the AI-RL sequence as it is under the RL-AI condition. It is hypothesized that training under the sequence RL-AI will produce superior transfer as detected by performance and efficiency measures on the transfer task.

Extending the above argument to the unmixed paradigms (RL-RL and AI-AI), it would seem that Ss under the RL-RL method would experience not only greater ease of acquisition on training compared to Ss under the AI-AI sequence but also would have greater separation and distinction of the conceptual components due to increased understanding and availability of the "given" component. Again, this clearer appreciation of the nature of the tasks should produce minimal difficulty on the transfer task. A hypothesis would have to predict superior positive transfer for RL-RL trained learners compared to AI-AI trained Ss.

Further, if the Lee & Gagné (1970) result claiming greater transfer facilitation when components of their complex rule were learned symmetrically can be applied here, the integration of the conceptual components should be further facilitated when these components are acquired symmetrically. As has been pointed out, the components will be most distinct under those paradigms where Ss are given the easily-understood attribute rather than the complex rule. Hence, even though Ss under the CL-CL paradigm may well have the conditions most favorable for symmetric acquisition of the attribute and rule components, this effect is most likely overshadowed by the lack of component separation. The similarity of the learning tasks and the transfer task provides an opportunity for Ss under the CL-CL method to transfer their acquisition strategy. But, these strategies are most likely surface strategies based on incomplete comprehension of the two-component nature of the task to be solved. An appreciation of this two-component nature of the concept tasks would provide an opportunity for S to develop a CL strategy on the transfer task which would be more powerful than that used by Ss who have achieved criterion on two CL learning tasks with difficulty and remain unsure as to how they did it. The ease of understanding the given attributes coupled with the greater ease of acquiring the rule should provide _Ss_ under the RL-RL condition with both good component separation and relative symmetry of learning. As previously noted, _Ss_ under the RL-AI first learn the rule and then have it clearly stated for them in instructions on the second task (AI). Component separation and symmetry of learning should be good in this condition too. It is hypothesized therefore that training under the RL-RL and RL-AI paradigms will provide an opportunity for development of a clearer, more efficient strategy for acquisition on the transfer task than those _Ss_ under the other learning conditions, including CL-CL.

The common transfer task is different from all the training tasks yet employs familiar stimulus materials. This is easily accomplished by using the same stimuli but using a new combination of relevant attributes, a new number of relevant attributes, and a new rule.

II. Method:

Design:

The experimental design was a 5 (repeated-measures) x 6 factorial. All _Ss_ received two warm-up tasks. Except for _Ss_ assigned to the empty or base-line condition, all _Ss_ came to criterion on two training tasks. The empty condition contained two filler tasks in place of the training tasks. All Ss under all conditions then performed on a common transfer task under the CL paradigm. However, the analysis of training

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Insert Figure 1 about here

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effects on transfer was carried out considering the two training tasks as levels of two factors in a modified 2 x 2 factorial design. One bi-levelled factor in this modified design is acquisition method on training task 1 (AI or RL) and the second factor is acquisition method on training task 2 (AI or RL). All possible combinations of first-learning method and second-learning method on the components could thus be tested for effects on the common transfer task. Additional cells representing the CL-CL and empty or base-line conditions were, of course, included.

Insert Figure 2 about here

The structures of all tasks used in the study are presented in Appendix A. Both of the learning tasks employed

Training Paradigm	Warm - Up 1	Warm - Up 2	Training Task 1	Training Task 2	Transfer Task
CL - CL					
AI - AI					
AI - RL					
RL - AI					
RL - RL					
Empty			Filler	Filler	

Figure 1. Diagrammatic representation of the full experimental design

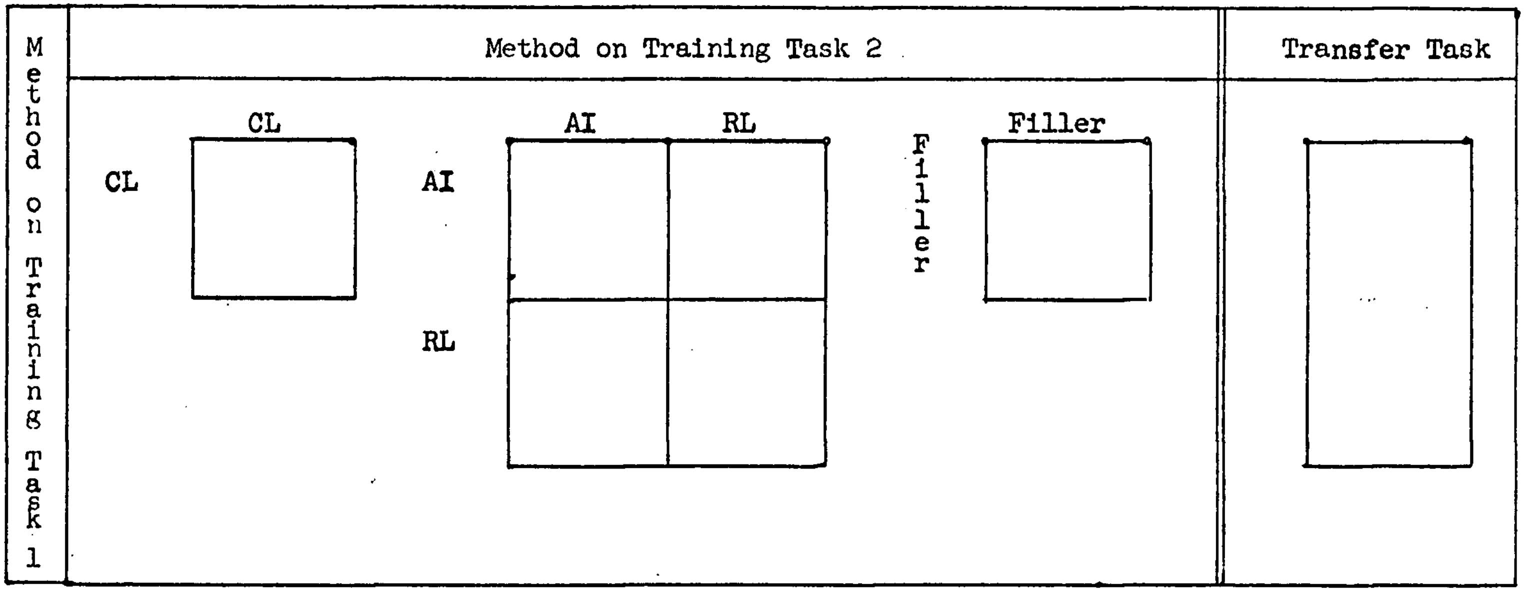

Figure 2. Diagrammatic representation of the experimental design as considered for analysis of training effect on transfer

a simple biconditional rule (the joint presence or the joint absence of the two relevant attributes constituted a positive instance of the concept) but used different dimensions and relevant values of those dimensions. For example, if the attributes shape and colour were relevant, in training task 1 the presence of red triangles and the absence of red triangles would constitute a positive instance of the concept. Other-coloured triangles and red shapes other than triangles constituted a negative instance of the concept. Since the rule was identical for both training tasks 1 and 2, all Ss were given instructions suggesting that the second of these tasks was another new task requiring another unique solution. Such instructions were considered to assist in preventing the formation of a set or suspicion that application of the first learning task role to the second task would automatically be successful. These instructions applied to Ss under the AI condition on task 2 even though it should have been obvious to them that the rule was identical (by instruction) for both training tasks.

Ss in all conditions were given two warm-up tasks, one common to all paradigms and the second paradigm-specific. Those Ss in the empty or base-line condition were given the warm-up tasks and the transfer task. They were given two filler tasks in an attempt to provide some degree of stimulus familiarization and warm-up comparable to that experienced by the Ss on the training tasks. A pilot project (N = 30) was carried out. The average length of time spent on the materials used on training tasks 1 and 2 was found to be 954 seconds. It was decided that filler tasks 1 and 2 would each be 16 minutes (960 seconds) in duration. The filler tasks consisted of verbally describing the values of five of the eight bi-levelled dimensions on the stimulus cards, announcing only values not shown on the card presented. For example, if the stimulus card should contain two large red outlined triangles on a white background with a solid border, a response by S "one small blue circle on a grey background" would be satisfactory. It is argued that this task not only provides approximately the same amount of experience and familiarization with the stimulus materials but also requires approximately the same degree of concentration on those materials that Ss under the training conditions would be expected to put into their tasks.

The transfer task consisted of three relevant dimensions and a contingent biconditional rule. The joint presence or the joint absence of two attributes contingent upon the presence of a third attribute constituted a positive instance of the concept (see Appendix A). The transfer task was carried out under the CL condition for all Ss in all paradigms.

In each task, three random orders of the 16 stimuli were prepared to prevent serial learning from taking place. The number of positive and negative instances of the concept were balanced in the warm-up and training tasks by the very nature of the rules used. However, because of the nature of the contingent biconditional rule used in the transfer task, only 6 positive instances of the 16 stimuli occurred naturally. The number of positive and negative instances per trial were balanced on the transfer task by the random deletion of two negative stimuli and their replacement with two additional, redundant, positive stimuli selected at random from the 6 positive instances. This process was carried out independently on the three random orders prepared.

The dependent variables measured were the number of trials to criterion (n), the number of errors to criterion (e), and the time taken to reach criterion (t). Since each of the n trials contained 16 cards, a total of 16n cards were viewed by each S. The ratio e/16n thus provides a measure of the error rate (ER). The measures n, e, t and ER will be used as indicators of acquisition performance. The actual time taken compared to the total time available to reach criterion produces a time rate (TR) measure. Since 15 seconds was the established interval per stimulus card (by instructions to S - see Appendix B), then the total available time to reach criterion is determined by the product of 16n cards and 15 seconds per card. The time rate measure TR is therefore $t/16n \times 15$. This measure should reflect time-related strategy styles employed by S during acquisition. It is argued that if S made full use of the information provided by E and the stimulus card presented (indicating a positive instance of the concept), TR would approach 1. If, however, S's strategy was to proceed through the stimuli rapidly, viewing as many as possible and making minimal use of the available information, his TR measure would necessarily be very small. While TR is no doubt related to cognitive style, it is considered here to reflect only the time aspects of strategy rather than provide a measure of holistic vs. analytic strategy, for example. Finally, two transformations on the three dependent variables were performed to arrive at measures that are to be interpreted in terms of acquisition efficiency. The product of ER and t yields a measure of the estimated average time spent making errors (ET) during acquisition tasks. This is a comprehensive measure insofar as it simultaneously considers n, e, and t. If e and t become large, so does the measure ET (since n must necessarily get proportionately large if e becomes large). The quotient resulting from the division of ET by the total available time (16n cards x 15 seconds/card) yields an estimate of the proportion of total available time spent making errors. This measure was analyzed as an efficiency measure to indicate how Ss under various conditions partitioned their available time during acquisition.

Subjects:

The Ss were 72 grade 9 and 10 students drawn from a subpopulation of 397 senior students in a local metropolitan Junior Secondary School. Students were asked to volunteer. From the population of positive responses to this invitation, a sample of 36 male and 36 female Ss was composed by random selection. These Ss were then assigned randomly to the six treatment conditions, the only restriction being an equal number of male and female Ss within each treatment group.

Stimulus Materials:

The stimuli were $2\frac{1}{2}$ x $3\frac{1}{2}$ in. 37-point paperboard cards on which geometric figures varying along eight bi-levelled dimensions had been hand printed using the silkscreen process. The dimensions and their values are: number of figures (one - two), shape of figures (triangle - circle), color of figures (blue - red), outline of figures (outline - no outline), background color (white - grey), border type (solid - broken), texture of figures (solid - slashed), and size of figures (large - small). Since each of these dimensions consists of two values, a total of $2^4 = 16$ cards constitutes the stimulus population if four dimensions are held constant in any given task. The number of cards presented per trial was therefore 16, a number of stimuli well in excess of the immediate memory span. Three orders of each trial of 16 stimulus cards were prepared to prevent serial learning from taking place. The number of positive instances were equated with the number of negative instances for each trial in each task. On the transfer task, this was accomplished by randomly deleting two negative stimuli per trial and substituting two randomly-selected, redundant positive stimuli. This was carried out independently for the three orders prepared on the transfer task.

Apparatus:

A black box measuring $9\frac{1}{2}$ x $9\frac{1}{2}$ x 34 in. was placed between E and S on a desk. An opening measuring the size of a stimulus card was at eye-level for each S. The box contained an electric motor operating at 60 rpm which when started passed through a cycle before shutting itself off. The cycle included the displacement of the card appearing in the window and its replacement with the next card held in a wooden supply box measuring $2\frac{1}{2}$ x $3\frac{1}{2}$ x 8 in. The motor inside the box could be activated by a push-button mounted on a small portable wooden box conveniently placed for S.

Procedure:

Written instructions were given to each S two days before the appointed time when possible (see Appendix B). Those Ss who had Monday appointments received their written instructions on the previous Friday whereas Ss having Tuesday appointments received their written instructions only the day before. Each S was instructed on the definition of dimension and value and was asked to give written examples (filling in blanks) following this instruction by observing two contrasting sample "cards" (diagrams) containing between them all eight dimensions and sixteen values possible. Just prior to the start of the experiment, a box-type diagram illustrating the bilevel nature of the eight non-labelled dimensions was presented to S in conjunction with a subsequent brief verbal lesson by E on the meaning of terms. E then read aloud the eight dimensions and S was required to provide verbally the two values per dimension while observing two contrasting sample cards. This procedure was designed to ensure a considerable degree of familiarity with the attributes of the various learning tasks. S was then instructed that in each of the learning tasks he would consider, he was to classify each card appearing in the window before him into two categories by using verbal responses. To ensure minimal interference between tasks resulting from response labels, specific names for the two classification categories were different for each task and S was informed of the verbal labels in the specific instructions for each task. A sample card constituting a positive instance of the required concept was provided for each S in all tasks and conditions. He was informed that the card belonged to the category whose label specified the positive instance of the concept only. In each task under all conditions, S also was provided with the names of the total number of varying dimensions (both relevant and irrelevant). In the AI condition, S was informed by E of the exact nature of the rule that would permit solution of the problem. In the RL condition, S was informed of the names of the relevant attributes (dimensions) as well as the names of the four varying dimensions. In the combined AI-RL condition, S was given the AI instructions for training task 1 and the RL instructions for training task 2. Ss in the CL condition were given only the names of the four varying dimensions. In each treatment condition, the stimulus materials (set B and set D - see Appendix A) were counterbalanced across the two training tasks and across sex.

After each response made by S, E provided verbal feedback by saying "right" or "wrong" under all tasks and conditions. S had a maximum of 15 seconds to observe each stimulus card and could present the next card by pressing the advance button himself. Accuracy and speed were considered of equal importance in the instructions to S. The concept was considered to be learned when S could perform perfectly on a given trial of 16 stimuli. On the two learning tasks, three random orders of each learning trial of 16 stimuli were prepared to prevent serial learning from taking place.

For Ss assigned to the empty condition, no instructions regarding dimensions or rule linking values of dimensions on the filler tasks were provided. The amount of time permitted on the filler tasks was 16 minutes each on the materials of set B and D (the stimuli used in the training tasks). As previously mentioned, this was established as the result of a pilot study. The average time spent on training task 1 was 1462 seconds and 668 seconds on training task 2 in this study. The average time spent on the materials of set B and set D was therefore 1065 seconds, 105 seconds more than the 960 seconds allowed the Ss for familiarization with the materials of sets B and D.

Finally, each S under each treatment condition was required to come to criterion on the transfer task. The same instructions were read to all Ss on this task. All Ss under all conditions learned the transfer task under the CL paradigm. Hence, the same instructions were read to all Ss on this task informing them only of the four varying dimensions by name and these names were again left in view for S. A sample card representing a positive instance of the concept was presented to each S and left in view throughout the learning trials.

III. Results:

A univariate and multivariate analysis of variance were performed on the seven dependent measures of the transfer task, first acquisition task, and a transformation of the training task 1 and 2 scores. A total of 75 Ss attempted the experiment but 3 of these were rejected because of inability to complete either a training task or the transfer task within one hour. Two of those rejected were on the CL-CL condition and the third was under the AI-AI paradigm. The acquisition measures of the remaining 72 Ss, 12 in each condition, were then considered in the analysis.

In the sample correlation matrix of the seven dependent variable measures on the transfer task (see Appendix D), the time ratio (TR) measure had the lowest correlation with performance measures n and e (in the order of .23 and .38 respectively). This lends support to the contention that TR reflects an aspect of acquisition behavior different from n and e. TR is considered an indicator of time-related strategy. The proportion of total time available spent making errors (ETPR) had a correlation in the order of .37 with n and .58 with e over all Ss on the transfer task.

However, a correlation of ETPR with TR of .935 indicates that both TR and ETPR reflect strategy and the resultant efficiency. Even though the efficiency measures ET and ETPR are highly correlated with the strategy measure TR as would be expected, strategy effects and efficiency effects will be discussed separately in the interpretation of results. It must be noted that measure ET is an estimated measure of the average time spent making errors. This measure could be improved by measuring automatically the actual time spent by S on each stimulus from which the time spent making errors could be found. Such precise measurement might well provide a more enlightened picture of comprehensive acquisition performance.

A series of planned orthogonal contrasts were used to test the research hypotheses. The first series of contrasts (see Appendix E for the optional contrast matrix) were designed to test hypotheses relating to the effects of learning paradigm on transfer performance, strategy, and efficiency. A contrast comparing the effects on transfer of previous training and minimal prior training showed a beneficial performance effect on measure e (Stepdown $F_{1,66} = 13.162$, p less than .0006) for previous training (see Appendix F). A similar beneficial effect on measure n just failed to reach significance (α = .05). This comparison did not indicate any beneficial transfer effects in terms of strategy or efficiency resulting from prior training in concept acquisition generally. However, when transfer performance resulting from CL-CL training was orthogonally contrasted with the transfer performance resulting from component-paradigm learning, the ETPR measure was found to be significantly different (Stepdown $F_{1,66}$ = 14.09, p less than .0004), indicating inferior efficiency on the transfer task for the CL-CL trained Ss compared to component-paradigm learners (see Appendix F). This result lends some support to the prediction made that due to a lack of component separation the performance and efficiency of Ss trained under the CL-CL paradigm would be substantially poorer than the transfer performance and efficiency observed for Ss trained under the component paradigms. Neither the strategy measure TR nor any of the performance measures reached significance but some trends in the predicted direction can be observed in the cell means (see table 1).

Insert table 1 about here

Table 1

Observed Cell Means of Seven Response Measures on

the Transfer Task (N = 72)

Training Paradigm	n	e	t	ER	TR	ET	ETPR
CL - CL	10.7	42.0	1215	.21	.41	327	.09
AI - AI	11.3	47.0	922	.24	.32	259	.08
AI - RL	9.0	32.6	1075	.21	.32	272	.10
RL - AI	10.3	33.3	600	.19	.25	130	.05
RL - RL	8.5	27.9	589	.18	.31	120	.06
Empty	13.2	35.7	841	.18	.27	147	.05

Performance measures are n (trials to criterion), e (errors to criterion), t (time to criterion) and ER (error rate)

Strategy measure is TR (time rate = t/240n)

Efficiency measures are ET (estimated mean time spent making errors) and ETPR (proportion of total available time spent making errors).

The hypothesized beneficial effect of symmetric acquisition of the conceptual components on transfer was not supported by the analysis. Transfer performance, strategy, and efficiency measures resulting from Ss whose previous experience had been on the symmetric AI-RL, RL-AI, and CL-CL paradigms was not different from transfer performance of Ss whose prior experience was under the asymmetrical AI-AI and RL-RL conditions. However, differential effects on transfer resulting from learning under the sequences AI-RL and RL-AI were observed on measures TR and ETPR indicating differing transfer strategies employed resulting from the training sequence on these paradigms. The RL-AI trained Ss presumably used a more efficient strategy than did the AI-RL trained Ss on the transfer task (see Appendix F). The efficiency measure ETPR on the contrast just mentioned was significant ($F_{1,66} = 4.005$, p less than .0495) as was performance measure (Stepdown $F_{1,66} = 5.804$, p less than .0189) with $\alpha = .05$. These results lend strong support to the hypothesis and prediction made relating to the effects of component order in these paradigms on transfer.

With regards to the unmixed paradigms AI-AI and RL-RL, the predicted beneficial effect of RL-RL training on transfer was supported by the comprehensive measure ER ($F_{1,66} = 3.997$, p less than .0497) but the performance measure e failed to reach significance ($F_{1,66} = 2.91$, p less than .0926) with $\alpha = .05$.

An additional series of three planned orthogonal contrasts was used to analyze the component-paradigm learning effect on transfer (see Appendix G). One such contrast on transfer measures of RL-AI and RL-RL trained Ss with AI-AI and AI-RL trained Ss showed very clearly the beneficial effect on transfer of the RL-first condition in training. The performance measures (except n) reached significance (α = .05) (see Appendix H). This result provides very strong support for the contention made that in RL-first paradigms, S would more easily understand the given component (attributes) than in the AI-first paradigms. This hypothesis is further supported by the results as the two efficiency measures ET and ETPR were both significant in the direction predicted. In addition, the strategy measure TR just failed to reach significance with $\alpha = .05$ ($F_{1,44} = 3.001$, p less than .0903) (see Appendix H). A contrast designed to test the effect of the second-training task acquisition method on transfer indicated no significant differences or effect on transfer performance, strategy, or efficiency resulting from second-task method in the training sequences. Similarly, when transfer performance resulting from training on the mixed paradigms (AI-RL and RL-AI) was contrasted with transfer performance on the non-mixed sequences (AI-AI and RL-RL), no differences could be detected on any of the measures of transfer (see Appendix H).

In the analysis of transfer within treatment groups from the first to second training task under component paradigms (see Appendix K for the optional contrast matrix), Ss who learned under the AI condition on task 1 experienced greatest positive transfer to task 2 (either AI or RL on task 2). This effect was indicated on measures e and ET (see Appendix L). A minimal within-treatment transfer effect was detected on training paradigms that had RL first. This is not surprising since the greater difficulty experienced under the task 1 AI condition would produce an opportunity for greater change (i.e., improvement) in performance on training task 2 than would the reverse sequence (RL-AI or RL-RL). The negative means shown in table 2 (RL-AI) for the within-transfer effect reflect the increased difficulty experienced by Ss when undertaking an AI task following a RL task. This is not unexpected.

Table 2

Observed Cell Means of Seven Transformed Response Measures*

on Within-Transfer (N = 60)

Training Paradigm	n	e	t	ER	TR	ET	ETPR
CL - CL	14.9	97.0	1434	.12	.007	595	.05
AI - AI	8.3	51.5	716	.08	.002	271	.03
AI - RL	12.4	87.1	10009	.14	-.003	462	.05
RL - AI	1.6	1.3	63	-.02	-.024	-11.9	-.02
RL - RL	8.2	45.8	584	.10	.013	201.3	.03

Performance measures are n (trials to criterion), e (errors to criterion), t (time to criterion) and ER (error rate)

Strategy measure is TR (time rate = t/240n)

Efficiency measures are ET (estimated mean time spent making errors) and ETPR (proportion of total available time spent making errors).

* The transformation of response measures consisted of taking the difference on each measure between Task 1 and Task 2.

Insert Table 2 about here

In absolute terms, the minimal transfer from task 1 to task 2 under the RL-AI and RL-RL paradigms reflects overall superior performance on both tasks 1 and 2 with the resultant minimal improvement from task 1 to task 2. For example, the mean number of errors to criterion on task 1 under the RL-RL and RL-AI conditions were 60 and 66 respectively compared to 124 and 107 under the AI-RL and AI-AI paradigms respectively (see Table 3).

Insert Table 3 about here

The within-group transfer effect was compared across the RL-AI and RL-RL paradigms. As shown in Appendix L, the greater positive transfer here was observed in the RL-RL sequence on the ER measure ($F_{1,55} = 5.189$, p less than .027). Measure e just failed to reach significance with $\alpha = .05$ ($F_{1,55} = 3.198$, p less than .079). This too is not unexpected since the task similarity (including the use of identical rules) would enable S to transfer the rule acquired under task 1 directly to task 2 in the RL-RL paradigm. The slightly negative transfer to task 2 in the RL-AI sequence (see Table

Table 3

Observed Cell Means of Seven Response Measures on

Acquisition Task 1 (N = 60)

Training Paradigm	n	e	t	ER	TR	ET	ETPR
CL - CL	25.6	137.8	2464	.35	.43	847	.15
AI - AI	19.9	106.8	1412	.33	.30	479	.10
AI - RL	20.3	123.7	1656	.39	.33	654	.14
RL - AI	12.8	66.3	933	.31	.31	313	.10
RL - RL	11.9	59.9	842	.30	.29	266	.09

Performance measures are n (trials to criterion), e (errors to criterion), t (time to criterion) and ER (error rate)

Strategy measure is TR (time rate = t/240n)

Efficiency measures are ET (estimated mean time spent making errors) and ETPR (proportion of total available time spent making errors).

2) indicates a balanced or symmetric acquisition of components, the tasks being of greater equality of difficulty when presented in this order.

In transfer to task 2, the effect of learning task 1 under CL was contrasted to the effect of learning task 1 under an acquisition component (AI or RL). The larger transfer effect was observed on performance measures n, e, t, and ET where first-task learning was under a component (see Appendix L). The minimal improvement on task 2 under the CL-CL condition was expected since component separation and distinction in this paradigm was hypothesized to be small compared to component separation and distinction in the component paradigms.

Measures of acquisition performance on training task 1 were analyzed using a univariate and multivariate analysis of variance. Again, planned orthogonal contrasts were used to test the research hypotheses (see Appendix I). As expected, performance under single-component acquisition was very superior to acquisition performance under the CL condition. For example, both measure e and t were highly significant ($F_{1,55} = 9.53$, p less than .0032 and $F_{1,55} = 25.560$, p less than .0001 respectively). The efficiency and strategy indices also exhibited significant superiority of performance for <u>S</u>s under a component condition rather than the CL condition (see Appendix J). The measure ETPR reached significance ($F_{1,55} = 5.63$, p less than .0212) whereas TR analysis indicated that TR also was highly significant ($F_{1,55} = 12.925$, p less than .0007). Further, comparison of acquisition performance between the AI and RL conditions on training task 1 showed the marked superiority of performance and efficiency expected on the RL condition. The measure e in this orthogonal contrast achieved $F_{1,55} = 13.648$ with p less than .0006. Measures n, t, ET, and ER also reached significance with $\alpha = .05$ (see Appendix J).

These results provide the support required to substantiate the basic theoretical structure from which the predictions and hypotheses resulted.

IV. Discussion:

Complete discovery learning of a concept as modelled on a complete-learning paradigm (CL) was found to be an inferior method of concept acquisition compared to "guided discovery" concept learning as modelled on component paradigms using attribute identification (AI) or rule learning (RL). Training on the whole-method of concept acquisition (CL) was also found to provide the poorest transfer to a new complex concept task compared to training where a component of the required concept was initially provided (AI or RL). An analysis of the effect of various component training paradigms on transfer demonstrated the superiority of RL-first paradigms over AI-first sequences. These results lent strong support to the predictive theory that in RL-first training sequences, S would understand the given attribute component better than he would in AI-first training paradigms. Providing S with the relevant conceptual attributes at the outset of a concept learning task not only provides for greater ease of concept acquisition (i.e., acquiring the necessary rule) but also provides for a beneficial transfer effect to a new complex concept.

These results tend to contradict the Guthrie (1967) conclusions. Guthrie concluded that Example learning and Example-Rule learning produced a superior transfer effect on a transfer task compared to no training or a Rule-Example training sequence. While the results of the present study would appear diametrically opposed to Guthrie's conclusions, it must be noted that the rules used by Guthrie were relatively simple compared to the complex rules used here. Guthrie used rules calling for the replacement of two letters or the transposition of two letters in a cryptogram. Also, the stimuli he used varied only along the size-of-word dimension. This raises the question of rule complexity as a determinant of transferability of acquired concepts to new concepts. The effect of the number of varying attributes in originally-learned concepts on transferability of those concepts to new complex concepts remains unanswered as well.

In addition, the present study demonstrated minimal within-group transfer from one training task to another under the CL-CL sequence. Training sequences employing component paradigms produced superior within-group transfer. These results supported a prediction based on a theory that component-paradigm learning would produce superior acquisition strategies that would, in turn, enhance acquisition performance on a new concept task.

V. Implications:

There are several implications of these results for the practical world of human instruction. If acquisition efficiency and high transferability to other concepts are to be maximized, the teacher must engineer the learning situation in order that the majority of concept acquisition takes place under the optimal acquisition and transfer conditions inherent in the RL-AI sequence. The conclusions reached here regarding the RL-AI learning sequence support the "discovery" method of learning, most easily adapted to the learning of scientific concepts in the laboratory. The clear presentation of relevant attributes in a skillful fashion by the teacher should enhance the initial acquisition of concepts by the students who must then go about "discovering" the rule for themselves. To complete the RL-AI sequence in a practical setting, it would both be feasible and advisable for the teacher to provide additional examples of the concept but in the reverse component order, subsequent to the students' acquisition under the RL condition. To give an example from the science area, concepts related to metric measurement could be taught under the optimal acquisition and transfer conditions by:

1. first presenting and verbally coding the relevant attributes-presenting each student with a metre stick, directing his attention to the marks and spaces between marks on the stick. As well as providing labels for communication, the verbal

coding of the relevant attributes with standard names such as millimetre and centimetre will enhance <u>S</u>'s ability to distinguish and separate the relevant attributes.

2. permitting each student to then "discover" the rule relating the attributes (mm to cm , cm to dm , dm to m , etc.). The teacher's role becomes one of providing feedback and provoking the desired responses from the students by questioning.

3. next presenting the student with the rule (just acquired) in a clear, definitive statement and permitting the student to engage in some identification of attributes. A simple example of this kind of activity would be the fill-in-the-blank type of task:

1 ______ = 10 mm; 1 cm = _______ mm; etc.

4. providing an opportunity for each <u>S</u> to practise using his new concept as a conceptual unit. For example, perhaps <u>S</u> could next be encouraged to devise his own "metric" system using as the standard of length a "XAT" stick provided by the teacher. Units of length known as millixats, centixats, decixats, and xats could be used to measure lengths of various objects.

The analysis of concept acquisition in terms of components AI and RL provides a framework within which not only concept research can be carried out but also within which the practical inter-relationship of the learner's and teacher's role in the acquisition of concepts can be considered.

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APPENDICES

Appendix A

Structure of Warm - Up, Training, and Transfer Tasks

Legend:

Color -- R for red	Border ----- B for broken
Shape -- T for triangle	Texture ---- S for smooth
Number - D for double	Background - W for white
Size --- L for large	Outline ---- O for outlined

Warm - Up and Training Tasks						Transfer Task	
Set:	A	B		C	D		E
R T D L	+	+	B S W O	+	+	D L W O	+
R T D $\overline{L}$	+	+	B S W $\overline{O}$	+	+	D L W $\overline{O}$	-
R T $\overline{D}$ L	-	+	B S $\overline{W}$ O	-	+	D L $\overline{W}$ O	+
R T $\overline{D}$ $\overline{L}$	-	+	B S $\overline{W}$ $\overline{O}$	-	+	D L $\overline{W}$ $\overline{O}$	-
R $\overline{T}$ D L	+	-	B $\overline{S}$ W O	+	-	D $\overline{L}$ W O	+
R $\overline{T}$ D $\overline{L}$	+	-	B $\overline{S}$ W $\overline{O}$	+	-	D $\overline{L}$ W $\overline{O}$	+
R $\overline{T}$ $\overline{D}$ L	-	-	B $\overline{S}$ $\overline{W}$ O	-	-	D $\overline{L}$ $\overline{W}$ O	+
R $\overline{T}$ $\overline{D}$ $\overline{L}$	-	-	B $\overline{S}$ $\overline{W}$ $\overline{O}$	-	-	D $\overline{L}$ $\overline{W}$ $\overline{O}$	+
$\overline{R}$ T D L	+	-	$\overline{B}$ S W O	+	-	$\overline{D}$ L W O	-
$\overline{R}$ T D $\overline{L}$	+	-	$\overline{B}$ S W $\overline{O}$	+	-	$\overline{D}$ L W $\overline{O}$	-
$\overline{R}$ T $\overline{D}$ L	-	-	$\overline{B}$ S $\overline{W}$ O	-	-	$\overline{D}$ L $\overline{W}$ O	-
$\overline{R}$ T $\overline{D}$ $\overline{L}$	-	-	$\overline{B}$ S $\overline{W}$ $\overline{O}$	-	-	$\overline{D}$ L $\overline{W}$ $\overline{O}$	-
$\overline{R}$ $\overline{T}$ D L	+	+	$\overline{B}$ $\overline{S}$ W O	+	+	$\overline{D}$ $\overline{L}$ W O	-
$\overline{R}$ $\overline{T}$ D $\overline{L}$	+	+	$\overline{B}$ $\overline{S}$ W $\overline{O}$	+	+	$\overline{D}$ $\overline{L}$ W $\overline{O}$	-
$\overline{R}$ $\overline{T}$ $\overline{D}$ L	-	+	$\overline{B}$ $\overline{S}$ $\overline{W}$ O	-	+	$\overline{D}$ $\overline{L}$ $\overline{W}$ O	-
$\overline{R}$ $\overline{T}$ $\overline{D}$ $\overline{L}$	-	+	$\overline{B}$ $\overline{S}$ $\overline{W}$ $\overline{O}$	-	+	$\overline{D}$ $\overline{L}$ $\overline{W}$ $\overline{O}$	-
Rule No.	1	3		2	4		5

Warm - Up tasks:

Rule No. 1 (Affirmation): The presence of two figures (D) constitutes a positive instance of the concept.

Rule No. 2 (Affirmation): The presence of white background (W) constitutes a positive instance of the concept.

Training tasks:

Rule No. 3 (Simple biconditional): The joint presence or the joint absence of red triangles constitutes a positive instance of the concept.

Rule No. 4 (Simple biconditional): The joint presence or the joint absence of a broken border and smooth-textured figures constitutes a positive instance of the concept.

Transfer task:

Rule No. 5 (Contingent biconditional): The presence of small figures or outlined figures, contingent upon the presence of two figures constitutes a positive instance of the concept.

APPENDIX B

Instructions to Subjects

I. General instructions (verbally presented by E):

Before we start, thanks again for coming and taking part in this experiment. Have you cleared with your regular teachers for the next two hours? Please do not discuss this experience with your classmates as we would like each of them to appear here "fresh" and without any bias. O.K.?

Please look at the two sample cards in front of you. They look familiar to you because they are the same as the diagrams you saw on the appointment sheet. When I read out the name of each of the dimensions, please tell me the values of that dimension. For example, when I say shape, you reply triangles and circles. Got that? Here we go. (E - check against the appointment sheet that S brought with him.)

Good. Now that we have that nice and clear, you are ready to play one of the five games we have prepared. In each game you are to classify cards into two categories by giving them verbal labels such as yes and no, positive and negative, and so on. I'll tell you what labels to use for each game. The cards you are going to categorize will appear in the window of the black box in front of you. To see the next card, simply push the button on the black wooden block.

When a card is in the window, study it with the other information you will have and try to decide what category it belongs to. You may respond as soon as you wish after the card appears up to a maximum of 15 seconds. I will tell you whether your answer is right or wrong. Once you know the correct category for the card, study it with the other available information you have before you advance the next card. Your accuracy is as important as your speed in all games.

In all games, you will be presented with the same deck of cards but in different orders until you are able to classify 16 cards correctly in one trial. When one sequence or trial of 16 cards has been presented, there will be a 20 second pause and then another sequence or trial begins. When you see an "end" card, press the advance button to clear it and wait for me to give you a go-ahead for the next trial.

Here are the specific rules for the first game. Before I give them to you, do you have any questions on this information? (to card # 1):-

<u>Card # 1</u>

<u>Set A</u> (Affirmation -- warm-up #1, common to all treatments.)

...only one dimension out of the four dimensions number, colour, shape, and size is important. Here is an example of a card which is a member of the "A" ("A" for affirmative) category. Say "A" for those cards you think belong in the same category as the example card and "N" ("N" for negative) for those you think belong in the other category. Use the sample card to help you figure out which category response to make to each card. Again, only one dimension out of these four is important.

(Back of Card #1): (Left in view for S)

NUMBER	COLOUR
SHAPE	SIZE

O.K. Here's game number (2, 3, 4, or 5). Again, in this game the cards will be presented one at a time and your task is to classify them into two separate categories.

Here is an example of a card which is a member of the (see code)* category. Say __________ for those cards you think belong in the same category as the sample card and __________ for those you think belong in the other category. Use the example card to help you figure out which category response to make to each card.

Again, I will tell you each time whether your answer is right or wrong. Speed is as important as accuracy in each game. Now, in this game, ... (to appropriate card):

* Responses:

Warm-up # 1 : "A" and "N" (affirmative and negative)

Warm-up #2 : "C" and "I" (correct and incorrect)

Learning Task #1 : "plus"and "minus"

Learning Task #2 : "yes" and "no"

Transfer Task : "positive" and "negative"

II. Specific instructions (verbally presented by E):

Card # 2 : instructions for CL on affirmation task (Warm-up # 2 - paradigm-specific)

Card # 3 : instructions for RL on affirmation task (Warm-up # 2 - paradigm-specific)

Card # 4 : instructions for AI on affirmation task (Warm-up #2 - paradigm-specific)

Card # 5 : instructions for CL on simple biconditional task (Learning task # 1)

Card # 6 : instructions for CL on simple biconditional task (Learning task # 2)

Card # 7 : instructions for RL on simple biconditional task (Learning task # 1)

Card # 8 : instructions for RL on simple biconditional task (Learning task # 2)

Card # 9 : instructions for AI on simple biconditional task (Learning task # 1)

Card # 10: instructions for AI on simple biconditional task (Learning task #2)

Card # 11: instructions for CL on modified contingent biconditional task (Transfer task)

Examples"

Card # 4: (Front)

Set C (AI on affirmation)

...one dimension of the four dimensions background, outline, border, and texture is important. Also, the rule is: the card with a particular value of the important dimension belongs in category "C".

(Back of Card # 4): (Left in view for S)

OUTLINE BACKGROUND

BORDER TEXTURE

Card # 7: (Front)

Set B (RL on simple biconditional)

...the "colour" and "shape" dimensions out of the four dimensions colour, shape, number, and size are important.

(Back of Card # 7): (Left in view for S)

COLOUR SHAPE

NUMBER SIZE

Card # 10: (Front)

Set D (AI on simple biconditional)

...two dimensions out of four dimensions (border, background, texture, and outline) are important.

Also, the rule is: the card with both a particular value of one dimension and a particular value of another dimension belongs in category "Yes". The card with the joint absence of both values also belongs in category "Yes". All other cards belong in category "No". Use this rule with two out of four of these dimensions.

(Back of Card # 10): (Left in view for S)

BACKGROUND | BORDER

TEXTURE | OUTLINE

Card # 11: (Front)

Set E (CL on modified contingent biconditional rule: Transfer task)

...three dimensions out of four dimensions number, size, background, and outline are important.

Again, three of these dimensions are important.

(Back of Card # 11) (Left in view for S)

SIZE | NUMBER

BACKGROUND | OUTLINE

III. General instructions (written, presented to S two days prior to the experimental trials).

Copies of the actual written instructions are presented for the next two pages.

APPENDIX C

Response Protocol Sheets

I. Response Protocol Sheet used for Warm-up tasks 1 and 2

II. Response Protocol Sheet used for Learning task # 1

III. Response Protocol Sheet used for Learning task # 2

IV. Response Protocol Sheet used for Transfer task

Research Project 599 Protocol 1

Subject Number: Date:

WARM - UP

Set "A" (D) Set "C" (S)

S responds: Affirmative/Negative S responds: Correct/Incorrect

card		1	2	3	4	5	card		1	2	3	4	5
16	N						10	I					
13	A						7	C					
9	A						8	C					
15	N						16	C					
7	N						1	I					
8	N						4	I					
3	N						3	I					
4	N						15	C					
2	A						5	C					
1	A						13	C					
11	N						14	C					
14	A						12	I					
5	A						2	I					
10	A						9	I					
6	A						6	C					
12	N						11	I					

Task time: ____________ mins. ______ sec. Task time: ____________ mins. ______ sec.

sch Project 599 Protocol 2

Subject Number: Date:

LEARNING TASK # 1

Set "B"
S responds: Plus/Minus

		1	4	7	10			2	5	8	11			3	6	9	12
4	+					16	+					12	-				
3	+					1	+					14	+				
10	-					2	+					10	-				
16	+					9	-					9	-				
7	-					3	+					6	-				
11	-					10	-					7	-				
13	+					4	+					3	+				
6	-					15	+					4	+				
9	-					5	-					16	+				
8	-					13	+					1	+				
5	-					11	-					11	-				
12	-					7	-					13	+				
1	+					8	-					15	+				
2	+					12	-					8	-				
15	+					6	-					5	-				
14	+					14	+					2	+				

Task Time: ______________ mins. ______________ secs.

Research Project 599 Protocol 3

Subject Number: 71 Date:

LEARNING TASK # 2

Set "D"
S responds: Yes/No

13

2	N	.				14	Y					4	N				
7	N	.				12	N					1	Y				
8	Y	.				11	Y					5	N				
14	Y	.				5	N					2	N				
15	N	.				4	N					6	Y				
3	Y	.				15	N					7	N				
4	N	.				16	Y					9	Y				
1	Y	.				6	Y					10	N				
6	Y	.				7	N					12	N				
10	N	.				2	N					8	Y				
12	N	.				1	Y					3	Y				
5	N	.				3	Y					13	N				
11	Y	.				8	Y					14	Y				
9	Y	.				9	Y					15	N				
13	N	.				10	N					16	Y				
16	Y	.				13	N					11	Y				

Task Time: ________ mins. ________ secs.

Research Project 599 Protocol 4

Subject Number: Date:

TRANSFER TASK

Set "E"
S responds: Positive/ Negative.

13

7	+					11	-					14	-				
1	+					7	+					1	+				
9	-					15	-					6	+				
3	+					5	+					7	+				
12	-					1	+					11	-				
16	-					8	+					8	+				
6	+					9	-					16	-				
2	-					3	+					5	+				
5	+					4	-					3	+				
8	+					2	-					15	-				
10	-					3	+					8	+				
6	+					6	+					4	-				
4	-					7	+					10	-				
13	-					14	-					5	+				
14	-					16	-					9	-				
1	+					13	-					12	-				

Task Time: __________ mins. __________ secs.

Appendix D

Sample Correlation and Intercorrelation Matrix of Seven

Response Measures on the Transfer Task (N = 72)

	n	e	t	ER	TR	ET	ETPR
n	1.000						
e	0.884	1.000					
t	0.695	0.765	1.000				
ER	0.462	0.764	0.580	1.000			
TR	0.226	0.382	0.811	0.445	1.000		
ET	0.637	0.791	0.978	0.674	0.805	1.000	
ETPR	0.366	0.576	0.873	0.689	0.935	0.907	1.000

Performance measures are n (trials to criterion), e (errors to criterion), t (time to criterion) and ER (error rate)

Strategy measure is TR (time rate = t/240n)

Efficiency measures are ET (estimated mean time spent making errors) and ETPR (proportion of total available time spent making errors).

Appendix E

Optional Contrast Matrix I Showing the

Contrast Coefficients Used in Testing Five

Contrasts of Response Measures on the Transfer Task

Contrast	CL-CL	AI-AI	AI-RL	RL-AI	RL-RL	Empty
1	1.0	1.0	1.0	1.0	1.0	-5.0
2	4.0	-1.0	-1.0	-1.0	-1.0	0.0
3	1/3	-1/2	1/3	1/3	-1/2	0.0
4	0.0	0.0	1.0	-1.0	0.0	0.0
5	0.0	1.0	0.0	0.0	-1.0	0.0

Appendix F

Univariate and Multivariate ANOVA on Seven Response Measures for Transfer Task Testing:

Contrast 1:	Training vs. no training.
Contrast 2:	CL vs. component learning.
Contrast 3:	Symmetric vs. asymetric acquisition of components.
Contrast 4:	AI-RL vs.RL-AI.
Contrast 5:	AI-AI vs.RL-RL.

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 1: Training vs. No Training)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	104.544	30.088	3.475	0.0668	3.475	0.668
e	7.803	750.164	0.010	0.9191	13.162	0.0006
t	15119.375	603240.000	0.025	0.8747	0.112	0.7387
ER	.011	0.005	2.190	0.1437	0.985	0.3247
TR	.060	0.031	1.940	0.1684	0.065	0.7995
ET	55576.988	61644.250	0.902	0.3459	0.651	0.4230
ETPR	.009	0.004	2.366	0.1288	-0.00	1.000

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 66

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 2: CL vs. component learning)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P<
n	8.681	30.088	0.2885	0.5930	0.2885	0.5930
e	660.061	750.164	0.880	0.3517	0.9651	0.3296
t	1142826.000	603240.000	1.8945	0.1734	1.0759	0.3035
ER	0.000	0.005	0.0586	0.8095	2.7285	0.1036
TR	0.0416	0.031	1.355	0.2486	0.1073	0.7444
ET	126505.063	61644.250	2.052	0.1567	0.2112	0.6475
ETPR	.002	0.004	0.456	0.5018	14.0943	0.0004

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 66

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 3: Symmetric vs. Asymmetric Acquisition of Components)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	.136	30.088	0.005	0.9466	0.0045	0.9467
e	33.000	750.164	0.044	0.8346	0.3278	0.5690
t	619677.938	603240.000	1.027	0.3145	3.1006	0.0831
ER	0.001	0.005	0.114	0.7367	0.0044	0.9476
TR	0.037	0.031	1.211	0.2752	0.2174	0.6427
ET	40768.129	61644.250	0.661	0.4191	0.0567	0.8126
ETPR	0.002	0.004	0.654	0.4218	0.2574	0.6139

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 66

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 4: AI-RL vs. RL-AI)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	9.375	30.088	0.312	0.5787	0.3116	0.5787
e	2.667	750.164	0.004	0.9527	0.8477	0.3607
t	1354222.000	603240.000	2.245	0.1389	5.8041	0.0189
ER	0.003	0.005	0.581	0.4489	0.2772	0.6005
TR	0.179	0.031	5.821	0.0187	0.0930	0.7614
ET	120699.750	61744.250	1.958	0.1664	1.7485	0.1910
ETPR	0.015	0.004	4.005	0.0495	-0.000	1.000

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 66

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 5: AI-AI vs. RL-RL)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P<
n	45.375	30.088	1.508	0.2238	1.508	0.2238
e	2185.044	750.164	2.913	0.0926	1.702	0.1966
t	664668.750	603240.000	1.102	0.2977	0.120	0.7299
ER	0.019	0.005	3.997	0.0497	0.803	0.3738
TR	0.002	0.031	0.048	0.8273	0.842	0.3624
ET	116343.063	61644.250	1.887	0.1742	1.579	0.2137
ETPR	0.005	0.004	1.392	0.2423	0.651	0.4232

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 66

Appendix G

Optional Contrast Matrix II Showing Orthogonal

Contrast Coefficients Used in Testing Three Additional

Contrasts of Response Measures on the Transfer Task (N = 48)

Contrast	AI-AI	AI-RL	RL-AI	RL-RL
1	1.0	1.0	-1.0	-1.0
2	1.0	-1.0	1.0	-1.0
3	1.0	-1.0	-1.0	1.0

Appendix H

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task testing:

Contrast 1: AI - first vs. RL - first.

Contrast 2: AI - second vs. RL - second.

Contrast 3: Unmixed paradigms (AI-AI; RL-RL) vs.mixed paradigms (AI-RL; RL-AI).

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 1: AI-first vs. RL-first)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	6.750	24.489	.276	0.6023	0.2763	0.6023
e	1017.520	675.185	1.507	0.2261	4.344	0.0432
t	1958186.000	468199.375	4.182	0.0469	1.499	0.2277
ER	0.018	0.004	4.396	0.0419	0.211	0.6482
TR	0.106	0.035	3.001	0.0903	2.844	0.0996
ET	237023.000	48550.724	4.882	0.0324	0.093	0.7617
ETPR	0.019	0.004	4.652	0.0366	0.600	0.4433

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 44

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 2: AI-second vs. RL-second)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	48.000	24.489	1.9601	0.1685	1.960	0.1685
e	1170.191	675.185	1.733	0.1949	0.000	0.9965
t	60704.602	468199.375	0.130	0.7206	2.983	0.0916
ER	0.004	0.004	0.883	0.3527	0.289	0.5936
TR	0.074	0.035	2.085	0.1559	0.876	0.3550
ET	20.019	48550.742	0.000	0.9839	3.582	0.0659
ETPR	0.001	0.004	0.310	0.5805	0.004	0.9501

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 44

Univariate and Multivariate ANOVA on Seven Response Measures of the Transfer Task

(Contrast 3: Unmixed paradigms AI-AI and RL-RL vs. Mixed paradigms AI-RL and RL-AI)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	0.750	24.489	0.031	0.8619	0.031	0.8620
e	247.521	675.185	0.367	0.5480	1.574	0.2164
t	79625.375	468199.375	0.170	0.6821	2.029	0.1617
ER	0.001	0.004	0.191	0.6641	1.600	0.2130
TR	0.009	0.035	0.243	0.6248	0.262	0.6114
ET	1530.009	48550.742	0.032	0.8600	0.005	0.9439
ETPR	0.001	0.004	0.196	0.6599	0.626	0.4337

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 44

Appendix I

Optional Contrast Matrix III Showing Orthogonal Contrast Coefficients Used in Testing Two Contrasts of Response Measures on Training Task 1 Under Five Learning Paradigms

Contrast	CL-CL	AI-AI	AI-RL	RL-AI	RL-RL
1	4.0	-1.0	-1.0	-1.0	-1.0
2	0.0	1.0	1.0	-1.0	-1.0

Appendix J

Univariate and Multivariate ANOVA on Seven Response Measures for Training Task 1 testing:

Contrast 1: CL vs. Component Learning.

Contrast 2: AI vs. RL.

Univariate and Multivariate ANOVA on Seven Response Measures of Training Task 1

(Contrast 1: CL vs. Component Learning)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P<
n	840.002	83.558	10.053	.0025	10.053	.0025
e	22737.090	2385.101	9.533	.0032	.235	.6302
t	15078606.000	589940.250	25.560	.0001	15.851	.0003
ER	.001	.006	0.214	.6458	0.129	.7213
TR	.130	.010	12.925	.0007	0.138	.7121
ET	1685720.000	88054.750	19.144	.0001	0.499	.4832
ETPR	.017	.003	5.635	.0212	1.029	.3154

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 55

Univariate and Multivariate ANOVA on Seven Response Measures of Training Task 1

(Contrast 2: AI vs. RL)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	728.519	83.558	8.719	.0047	8.7187	.0047
e	32552.078	2385.101	13.648	.0006	4.8147	.0326
t	5013609.000	589940.250	8.499	.0052	0.0020	.9641
ER	.031	.006	4.902	.0310	0.1089	.7428
TR	.003	.010	0.280	.5990	0.0028	.9582
ET	921854.063	88054.750	10.470	.0021	0.0445	.8339
ETPR	.006	.003	2.138	.1494	0.0614	.8053

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 55

Appendix K

Optional Contrast Matrix IV Showing Orthogonal Contrast

Coefficients Used in Testing Four Contrasts on

Within-Transfer (Training Task 1 - Training Task 2)

Under Five Learning Paradigms

Contrast	CL-CL	AI-AI	AI-RL	RL-AI	RL-RL
1	-4.0	1.0	1.0	1.0	1.0
2	0.0	1.0	1.0	-1.0	-1.0
3	0.0	1.0	-1.0	0.0	0.0
4	0.0	0.0	0.0	-1.0	1.0

Appendix L

Univariate and Multivariate ANOVA on Seven Response

Measures of Within - Transfer:

Training Task 1 - Training Task 2 testing:

Contrast 1: CL vs. component learning.

Contrast 2: AI-first vs. RL-first.

Contrast 3: AI-AI vs. AI-RL.

Contrast 4: RL-AI vs. RL-RL.

Univariate and Multivariate ANOVA on Seven Response Measures of Within-Transfer (Training Task 1 - Training Task 2)

(Contrast 1: CL vs. component learning)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	510.417	117.183	4.356	.0416	4.356	.0416
e	24543.059	3715.205	6.606	.0130	2.354	.1309
t	6791243.000	901076.438	7.537	.0082	1.935	.1701
ER	.015	.017	0.922	.3413	2.069	.1563
TR	.001	.010	0.091	.7641	1.025	.3161
ET	1270940.000	134041.250	9.482	.0033	0.256	.6151
ETPR	.008	.005	1.588	.2130	2.561	.1160

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 55

Univariate and Multivariate ANOVA on Seven Response Measures of Within-Transfer (Training Task 1 - Training Task 2)

(Contrast 2: AI-first vs. RL-first)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	362.999	117.183	3.098	.085	3.098	.084
e	25071.008	3715.205	6.748	.012	5.258	.026
t	3488404.000	901076.438	3.871	.054	0.016	.899
ER	.058	.017	3.480	.068	0.362	.550
TR	.000	.010	0.026	.873	0.856	.359
ET	888622.438	134041.250	6.630	.013	0.062	.805
ETPR	.010	.005	1.999	.163	0.410	.525

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 55

Univariate and Multivariate ANOVA on Seven Response Measures of Within-Transfer (Training Task 1 - Training Task 2)

(Contrast 3: AI-AI vs. AI-RL)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P <
n	100.042	117.183	0.854	0.3596	0.8537	0.3596
e	7597.027	3715.205	2.045	0.1584	1.9112	0.1726
t	513336.875	901076.438	0.570	0.4537	0.7255	0.3982
ER	0.022	.017	1.306	0.2580	0.0198	0.8886
TR	0.000	.010	0.020	0.8883	0.1801	0.6731
ET	219076.063	134041.250	1.634	0.2065	1.9499	0.1688
ETPR	0.003	.005	0.628	0.4317	0.5387	0.4665

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 5[illegible]

Univariate and Multivariate ANOVA on Seven Response Measures of Within-Transfer (Training Task 1 - Training Task 2)

(Contrast 4: RL-AI vs. RL-RL)

Variable	Hypoth. MS	MSE	Univ. F	P <	Stpdn. F	P<
n	260.041	117.183	2.219	0.1421	2.219	0.1421
e	11881.481	3715.205	3.198	0.0793	1.017	0.3177
t	1628642.000	901076.438	1.807	0.1844	0.244	0.6232
ER	.087	.017	5.190	0.0267	3.512	0.0667
TR	.008	.010	0.798	0.3755	0.001	0.9730
ET	272640.000	134041.250	2.034	0.1595	0.395	0.5324
ETPR	.012	.005	2.492	0.1202	0.872	0.3550

Degrees of freedom for hypothesis = 1

Degrees of freedom for error = 55