DOCUMENT RESUME

ED 097 592 95 CG 009 156

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TITLE Effects of Attribute Identification Pretraining on Rule Effects in Attribute Identification Transfer Tasks. Technical Report No. 278.

INSTITUTION Wisconsin Univ., Madison. Research and Development Center for Cognitive Learning.

SPONS AGENCY National Inst. of Education (DHEW), Washington, D.C.

REPORT NO WRDCCL-TR-278

PUB DATE Nov 73

CONTRACT NE-C-00-3-0065

NOTE 21p.

EDRS PRICE MF-$0.75 HC-$1.50 PLUS POSTAGE

DESCRIPTORS *Behavioral Science Research; High School Students; Learning Theories; Research Projects; *Response Mode; *Stimulus Behavior

ABSTRACT

An attempt was made to reduce or eliminate rule effects in attribute identification (AI) tasks through AI pretraining. Thirty-six 12th-grade volunteers received 0, 4, or 8 AI problems prior to transfer to a final AI task. Results showed that even at the highest level of pretraining, rule effects were present at transfer. These findings were discussed in terms of the possible factors contributing to AI rule effects. (Author)

ED 097592

Technical Report No. 278

EFFECTS OF ATTRIBUTE IDENTIFICATION PRETRAINING ON RULE EFFECTS IN ATTRIBUTE IDENTIFICATION TRANSFER TASKS

by

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Report from the Project on
Children's Learning and Development

CG 009 156

Wisconsin Research and Development
Center for Cognitive Learning
The University of Wisconsin
Madison, Wisconsin

November 1973

Published by the Wisconsin Research and Development Center for Cognitive Learning, supported in part as a research and development center by funds from the National Institute of Education, Department of Health, Education, and Welfare. The opinions expressed herein do not necessarily reflect the position or policy of the National Institute of Education and no official endorsement by that agency should be inferred.

Center Contract No. NE-C-00-3-0065

Statement of Focus

Individually Guided Education (IGE) is a new comprehensive system of elementary education. The following components of the IGE system are in varying stages of development and implementation: a new organization for instruction and related administrative arrangements; a model of instructional programing for the individual student; and curriculum components in prereading, reading, mathematics, motivation, and environmental education. The development of other curriculum components, of a system for managing instruction by computer, and of instructional strategies is needed to complete the system. Continuing programmatic research is required to provide a sound knowledge base for the components under development and for improved second generation components. Finally, systematic implementation is essential so that the products will function properly in the IGE schools.

The Center plans and carries out the research, development, and implementation components of its IGE program in this sequence: (1) identify the needs and delimit the component problem area; (2) assess the possible constraints—financial resources and availability of staff; (3) formulate general plans and specific procedures for solving the problems; (4) secure and allocate human and material resources to carry out the plans; (5) provide for effective communication among personnel and efficient management of activities and resources; and (6) evaluate the effectiveness of each activity and its contribution to the total program and correct any difficulties through feedback mechanisms and appropriate management techniques.

A self-renewing system of elementary education is projected in each participating elementary school, i.e., one which is less dependent on external sources for direction and is more responsive to the needs of the children attending each particular school. In the IGE schools, Center-developed and other curriculum products compatible with the Center's instructional programing model will lead to higher student achievement and self-direction in learning and in conduct and also to higher morale and job satisfaction among educational personnel. Each developmental product makes its unique contribution to IGE as it is implemented in the schools. The various research components add to the knowledge of Center practitioners, developers, and theorists.

Acknowledgment

The author is indebted to Mavis Blake for her assistance in preparing stimulus materials and serving as one of the experimenters.

Table of Contents

List of Tables

I
Introduction

Man organizes his complex environment by making the same response to certain non-identical stimuli. This mode of organizing and responding to our environment has been termed conceptual behavior. There are many types of concepts. Formally, a class concept can be defined as a rule or relationship between certain stimulus characteristics (relevant attributes) which results in the partitioning of the stimulus set into two or more groups. The simplest concepts generate two groups: those stimuli associated with the concept (positive instances), and those stimuli not associated with the concept (negative instances). It is with such two-group classifications that this paper is primarily concerned.

The important characteristics entering into the definition of a class concept are the relevant attributes and the logical rule. In a sense, these two aspects of any class concept are independent. For example, many different class concepts can be generated by requiring the joint presence of any of a number of different pairs of relevant attributes (e.g., one possible relationship is a conjunction: red *and* square, blue *and* triangular, yellow *and* hexagonal, etc.). Similarly, several different class concepts may be generated using the same two relevant attributes, but changing the relationship (e.g.: red *and* square; red *or* square *or both*; *if* red, *then* square, etc.). Given this essential independence of components, two main kinds of conceptual problems can be distinguished, attribute identification (AI) and rule learning (RL). In AI tasks *S* is given information about the rule and must identify the relevant attributes. In RL, the relevant attributes are specified for *S*; his task is to identify the relationship between them (the rule).

The rules mentioned above refer to a system of rules based upon the logical truth table and the calculus of propositions (Haygood & Bourne, 1965). Given that there are at least two dimensions with at least two values per dimension, the selection of the two relevant attributes (one attribute from each of two dimensions) reduces the entire stimulus population to four classes. For example, given the relevant attributes *red* and *square*, the resultant four classes become (a) those patterns which are both red and square, (b) those patterns which are red but not square, (c) those patterns which are not red but are square, and (d) those patterns which are neither red nor square. These four classes correspond to the logical truth table, in which the symbols T (true) and F (false) represent the presence or absence of the relevant attributes (Haygood & Bourne, 1965). Thus, the four classes outlined above can be described in more general terms as TT, TF, FT, and FF respectively.

It has been shown that of the 16 possible ways of assigning the four classes to the two response categories (Table 1), only ten are unique and non-trivial (Neisser & Weene, 1962; Haygood & Bourne, 1965). These ten are shown in Table 2. Two of the ten are unidimensional rules, based on the presence or absence of a single attribute: the Affirmative (Aff) rule and its complement, Negation (Neg). The remaining eight rules are bidimensional in nature, described by a relationship between an attribute from each of two dimensions: the Conjunctive (Cj), Inclusive Disjunctive (Dj), Conditional (Cd), and Biconditional (Bd), and their complements.

Tasks and Variables

Until recently, investigations of the acquisition and utilization of concepts were mainly concerned with the variables thought to affect AI performance. As a result, a number of variables, such as the effects of number of relevant or irrelevant dimensions

TABLE 1

SIXTEEN UNIQUE BIDIMENSIONAL PARTITIONS OF A STIMULUS POPULATION FORMING THE CALCULUS OF PROPOSITIONS

Truth-Table Class	Partition (Rules) Response Category Assignments	(Dj)		(Cd)				(Bd)				(Cj)				
TT	+	+	+	+	-	+	+	+	-	-	-	+	-	-	-	-
TF	+	+	+	-	+	+	-	-	-	+	+	-	+	-	-	-
FT	+	+	-	+	+	-	+	-	+	+	-	-	-	+	-	-
FF	+	-	+	+	+	-	-	+	+	-	+	-	-	-	+	-

TABLE 2

CONCEPTUAL RULES DESCRIBING BINARY PARTITIONS OF A STIMULUS POPULATION

Primary Rule: Name	Primary Rule: Symbolic Description[a]	Primary Rule: Verbal Description	Complementary Rule: Name	Complementary Rule: Symbolic Description[a]	Complementary Rule: Verbal Description
Affirmative	R	All red patterns are examples of the concept.	Negation	$\bar{R}$	All patterns which are not red are examples.
Conjunctive	$R \cap S$	All patterns which are red and square are examples.	Alternative denial	$R \mid S$	All patterns which are either not red or not square are examples.
Inclusive disjunctive	$R \cup S$	All patterns which are red or square or both are examples.	Joint denial	$R \downarrow S$	All patterns which are neither red nor square are examples.
Conditional	$R \rightarrow S$	If a pattern is red then it must be square to be an example.	Exclusion	$R \cap \bar{S}$	All patterns which are red and not square are examples.
Biconditional	$R \leftrightarrow S$	Red patterns are examples if and only if they are square.	Exclusive disjunctive	$R \bar{\cup} S$	All patterns which are red or square but not both are examples.

[a]R and S stand for red and square (relevant attributes).

(Bourne, 1957; Bulgarella & Archer, 1962; Walker & Bourne, 1961), response system complexity (Walker & Bourne, 1961; Kepros, 1965), stimulus redundancy (Bourne & Haygood, 1959), as well as intra- and interdimensional variability (Battig & Bourne, 1961), have been investigated in AI. In most studies performed prior to 1965, it was tacitly assumed that the underlying rule in the AI task did not affect the variables in question.

Haygood and Bourne (1965) were the first investigators to establish the independence of RL tasks and AI tasks. Proceeding from the assumption that there are two major components of any conceptual task (the relevant attribute[s] and the rule), Haygood and Bourne instructed independent groups of *S*s in two ways: one group of *S*s was given the relevant attributes and was required to learn the rule (RL), while a second group was given the rule and was required to identify the relevant attributes (AI). The major result of interest was that, given the relevant attributes, some rules were harder to identify than others and that the speed with which the important attributes (AI) were identified was greatly affected by the underlying rule. Establishing that RL and AI are independent tasks opened the way for a more thorough investigation of the variables thought to affect primarily RL or AI. Since Haygood and Bourne (1965), a number of studies have made it clear that the RL or AI tasks may reveal quite different functions under the manipulation of certain variables (e.g., type of stimulus information, or amount of relevant or irrelevant information).

Type of Stimulus Information

Bourne and Guy (1968b) investigated the effects of type of stimulus information (all positive instances, all negative instances, or mixed positive and negative instances) on RL and AI performance. Their findings indicated that in AI, performance was in general optimal when instances from the smaller, more homogeneous, category were presented. Category homogeneity depends upon the number of truth table classes that are contained in a response category. Homogeneity increases as the number of truth table classes involved in a single response category decreases. For example, the positive category is the most homogeneous for the Cj rule, because it contains only TT's, while the negative category contains three classes of instances (TF's, FT's, and FF's). Similarly, the negative category, containing only TF instances, is the most homogeneous for the Cd rule, while the positive category contains TT's, FT's, and FF's. Therefore, Conjunctive AI performance was optimal when all positive instances (TT's) were presented, while Conditional AI performance was best when all negative instances (TF's) were presented. RL performance, on the other hand, was best in all cases when *S* was presented with a mixed sequence of positives and negatives.

Bourne and Guy (1968b) explained the differing RL and AI results in terms of the unique requirements of each task. In RL, *S*'s task is to identify an unknown relationship between two particular attributes. Since this task involves learning the categorization of at least one instance from each truth table category, a mixed sequence of positives and negatives (containing TT's, TF's, FT's, and FF's) was more useful than a sequence of all positives or all negatives which necessarily contains some subset of the four truth table classes. In AI, on the other hand, *S*s must identify the unknown relevant attributes within the structure of a given rule. In other words, *S* must test a number of possible attribute combinations in order to reach solution. In this task, stimulus sequences from the smaller, more homogeneous category were the easiest since *S* was faced with fewer attribute combinations as well as fewer distinctly different patterns to remember.

Amount of Relevant or Irrelevant Information

Studies investigating a second variable, namely the effects of varying the amount of relevant or irrelevant information, have revealed different results under conditions of RL and AI. Kepros and Bourne (1966) demonstrated an increase in difficulty with increases in number of relevant or irrelevant dimensions in an AI task (based on the Bd rule). Furthermore, although several problems were given, no significant improvement was obtained with practice, indicating that the increased difficulty is a relatively stable phenomenon (at least for the number of problems given). Explication of these results can again be given in terms of the requirements of the AI task. In order to solve, *S* may have to test the relevance of each dimension. Increasing the number of dimensions (either relevant or irrelevant) increases the length of the testing process, thereby increasing task difficulty.

Logically, increasing the number of irrelevant (and possibly relevant) dimensions should not affect RL, since *S*s are told which dimensions are relevant at the outset of the problem. This information should eliminate the dimensional testing process described above in the context of the AI task. Experiments have, in general, supported the above analysis. Bower and King (1967) investigated increasing the irrelevant information in an RL task (*Ss* were each given three problems on the same rule). Increasing the number of irrelevant dimensions increased the difficulty of only the first problem, suggesting that some amount of practice (Problem 1) may be necessary for *Ss* to learn to ignore all but the relevant attributes. However, this practice may not always be needed. A similar study by Haygood and Stevenson (1967) varied the number of irrelevant dimensions (0, 1, or 2) under conditions of AI and RL. While the well documented decrement in performance with increases in the amount of irrelevant information was shown in AI, this manipulation had no significant effect in RL.

Rules

Previous experiments (Bourne, 1967, 1970; Haygood & Bourne, 1965; Bourne & Guy, 1968a; Conant & Trabasso, 1964; DiVesta & Walls, 1969) have shown that for a naive *S* the specific logical rule involved largely determines the difficulty of a problem (for both RL and AI). Furthermore, rule effects in both tasks are similar in form (the order of difficulty of certain rules is the same). There are at least two possible determinants of such rule effects in AI.

The first and most obvious possibility is that this ordering may be due at least partially to *S*'s difficulty in fully understanding the given rule from instructions. To illustrate, the information provided in AI is mainly information about the rule. It may be quite difficult for *S* to grasp the "givens" of the problem through instructions, and this may be especially true for more difficult rules. Therefore, during the AI task *S* may be placed in a situation in which he is not only trying to identify the attributes, but may also be attempting to completely understand the *rule*. It may be this residual rule learning which produces the effect. However, another study (Ingison, in preparation) designed to reduce or eliminate AI rule effects through pretraining on several RL problems failed to do so, despite the fact that *Ss* at the highest pretraining levels showed no rule effects by the final RL problem.

A second reasonable explanation of rule effects in AI tasks can be given in terms of *Ss*' familiarity with the AI task itself. It is possible that *Ss* require some amount of practice in applying a rule in AI problems, in order to reduce overall rule differences in AI. Optimal selection strategies specific to the underlying rule in the AI task have been identified; they develop with practice on successive problems involving the same rule (Laughlin, 1968; Laughlin & Jordan, 1967). This suggests that there might also be optimal reception strategies specific to each rule. The present experiment was designed to investigate this possibility. Subjects were trained on several AI problems in an attempt to reduce or eliminate rule effects on an AI transfer task.

II
Method

Subjects and Design

Subjects were 36 twelfth-grade volunteers from the public schools of a semi-rural community in Wisconsin. Each *S* was assigned by each *E* to one of six independent conditions by means of three randomized sequences designed to place one *S* in each cell before placing a second *S* in any cell. The experimental design was a 2(rules: Dj or Cd) x 3(pretraining levels: 0, 4, or 8 pretraining problems prior to a transfer AI task) x 2(experimenters) factorial. A total of three *S*s were assigned to each cell described by the design.

Materials

The stimulus population contained a total of 27 different stimuli, resulting from enumeration of three dimensions of three levels each. The specific dimensions and levels were size (large, medium, and small), shape (triangular, square, and hexagonal), and color (red, yellow, and blue). Example cards illustrating the rules involved for each AI problem were presented on 5" x 7" index cards.

Problems

Since a total of nine different problems was called for by the design, nine pairs of relevant attributes were chosen, one value from each of two dimensions. Selection of attributes was restricted to the use of each *dimension* six times and each *level* of any dimension twice. This procedure resulted in three solution types. In other words, out of the nine pairs of attributes required, three involved a color and a shape, three involved a color and a size, and three involved a size and a shape.

Further restrictions involved the order in which the problems were presented to *S*s. Two problems of the same type were not presented to *S* in succession; rather the three solution types were alternated (e.g., a color-shape, a size-shape, and a size-color). In addition, the problems for each pretraining condition were arranged in a manner such that the final problems prior to transfer involved the same relevant attributes. Table 3 presents the exact attributes relevant to solution, as well as the order in which each pair occurred.

One final consideration in the construction of the problems was the arrangement of stimulus sequences such that, theoretically, the informational content was the same per block of trials regardless of the rule involved. It can be demonstrated that different rules may require different numbers of trials to obtain sufficient information to solve an AI problem. Table 4 presents a step-by-step information analysis with specific examples. In the present study, sufficient information to solve an AI problem involving the Dj rule required at least four stimuli in order to present the theoretically minimum necessary information: a TF, an FT, and two FF's. The TF and the FT served to present the two relevant attributes as well as a certain amount of irrelevant information (the TF and FT were chosen so that their irrelevant values were not the same). The two FF instances logically eliminated all but the relevant attributes. For the Cd rule, two TF's and one TT theoretically present sufficient information to solve the problem. The two TF's were chosen to vary on dimensions other than the first T value, identifying the first relevant attribute (that attribute common to both TF's). The second function of the TF's was to identify four other attributes which must be irrelevant, by definition. The TT instance then identified the second relevant attribute, as it was chosen to contain an irrelevant attribute already omitted. Since it contained the first T value and was positive,

TABLE 3

RELEVANT ATTRIBUTES FOR EACH PROBLEM

	Number of Pretraining Problems 0	4	8	Relevant Attributes
	Problem Number			
Transfer Problem	1	5	9	Large Square
Pretraining Problems		4	8	Medium Triangle
		3	7	Yellow Hexagon
		2	6	Large Blue
		1	5	Small Red
			4	Medium Square
			3	Red Hexagon
			2	Blue Triangle
			1	Medium Yellow

TABLE 4

BASIC UNITS OF INFORMATION FOR EACH RULE UNDER AI

Rule	Basic Unit	Specific Example Stimuli	Steps in Logical Elimination
*Dj	TF +	Medium Blue Square	One or two of the attributes are relevant.
	FT +	Large Red Triangle	Because there is no overlap in attributes, one attribute from each pattern must be relevant.
	FF -	Large Blue Triangle	Since this stimulus is negative, it can contain no relevant attributes. Therefore, eliminate Large, Blue, and Triangle.
	FF -	Large Yellow Square	Similarly, eliminate Large, Yellow, and Square. The only attributes left are Medium and Red.
*Cd	TF -	Medium Blue Hexagon	One of the attributes is relevant.
	TF -	Medium Yellow Square	Color and shape vary, so Medium must be relevant.
	TT +	Medium Red Square	This stimulus is a positive instance that contains Medium. Therefore, it must be a TT, and contain the second relevant attribute. Since Square was present in a TF, the second relevant attribute must be Red.

*Solution for all examples is Medium Red.

TABLE 5

UNITS OF INFORMATION AND RESPONSE ASSIGNMENTS FOR EACH RULE

Dj		Cd	
1. TF +	Basic unit	1. TF -	Basic unit
2. FT +		2. TF -	
3. FF -		3. TT +	
4. FF -		4. FT +	
5. TT +		5. FF +	
6. FF -		6. TF -	
7. TF +		7. FF +	
8. FF -		8. TF -	

it was by definition a TT instance, and *S* could identify the second relevant attribute by elimination.

Stimulus sequences were constructed using the constraints described below. The minimum stimuli theoretically necessary to solve each problem were identified. These basic units were expanded to form informational units by the following manipulations. Each informational unit contained at least one instance of each truth table category and an equal number of positive and negative instances. In addition, the informational units for each rule were required to be equal in length. The resulting information units were eight trials long. Table 5 presents the basic and informational units for both rules.

Procedure

Subjects were tested individually. Instructions were read to each *S* and, in addition, appropriate example cards were provided by *E*. Stimuli were presented on slides and projected by means of a carrousel projector.

A modified reception paradigm was employed in which sets of trials with the answers given (study trials) were alternated with sets in which *S* was required to classify each pattern (test trials). Eight study trials (one complete informational unit) alternated with four test trials (one from each truth table class) throughout the problem. The *S*s responded verbally on test trials, and *E* provided feedback for *S*. Each slide remained on the screen for approximately 4-5 seconds. The *S*s were given up to 72 test trials on each problem to reach a criterion of 16 correct test trials in a row. Those *S*s not reaching criterion at this time were given the solution by *E* and required to demonstrate this solution by reaching the criterion of 16 correct. At this time, *S* was taken to the next problem. Thus, no *S*s were eliminated from the analysis. Table 6 shows the number of *S*s failing to reach criterion in 72 test trials on each problem.

TABLE 6

THE NUMBER OF SUBJECTS FAILING TO REACH SOLUTION

Pretraining Condition	Rule					
	Dj			Cd		
		Problem Number	Number Failing		Problem Number	Number Failing
Zero Pretraining Problems		1.	0		1.	1
Four Pretraining Problems		1.	2		1.	5
		2.	2		2.	4
		3.	0		3.	3
		4.	0		4.	4
	Transfer Task	5.	0	Transfer Task	5.	1
Eight Pretraining Problems		1.	2		1.	5
		2.	0		2.	2
		3.	0		3.	0
		4.	0		4.	2
		5.	0		5.	2
		6.	0		6.	1
		7.	0		7.	1
		8.	0		8.	1
	Transfer Task	9.	0	Transfer Task	9.	0

III
Results

Results were analyzed first in terms of performance on the final (transfer) AI problem. In addition, performance across pretraining problems was assessed. Four dependent measures were used: total trials to the last error, total errors, total trials to the last error on each truth table class, and total errors for each truth table class. The degree to which the variables of sex and experimenter contributed to the overall variance was assessed by means of a 3(pretraining levels) x 2(rules) x 2(sexes) x 2(experimenters) analysis of variance on total final problem errors. Further, a 2(rules) x 2(sexes) x 2(experimenters) x 5 or 9(problems) repeated measure factorial was performed. No main effects or interactions involving either sex or *E* obtained significance in the analyses. Data from both *E*s and both sexes were pooled for all further analyses.

The results of the total trials to the last error and total errors analyses in no way contradicted the results of the measures involving truth table as a variable. Therefore, since truth table effects are generally interesting, only the results of those analyses in which truth table is included as a variable will be reported here. In addition, because the errors analyses were more sensitive than the trials analyses (although they in no way contradicted them), only the results of the errors analyses will be reported.

Final Problem Analysis

Performance on the final AI problem was analyzed by means of a 3(pretraining conditions) x 2(rules) x 4(truth table classes) repeated measures analysis of variance. Contrary to the prediction that increasing amounts of AI training would significantly reduce or eliminate rule effects in AI, the interaction of pretraining and rule did not reach significance $F(2,30) = 1.57$, $p < .22$, indicating that performance of *S*s at all pretraining levels was similar. Further, no linear trend was apparent for this effect.

The main effect of pretraining, $F(2,30) = 8.84$, $p < .001$, reached significance in almost all analyses. Error means at each pretraining level were 13.83, 5.75, and 4.58 for the 0, 4, and 8 pretraining problems conditions respectively. Tukey HSD tests were computed, revealing significant differences only between the 0-problem condition and all others, $p < .01$. It would appear from these data that as few as four AI pretraining problems are sufficient to reduce errors significantly on subsequent AI tasks.

The main effect of rule also attained significance, $F(1,30) = 5.97$, $p < .02$. Error means for each rule are 1.42 (Dj) and 2.61 (Cd), revealing the difficulty of the Cd rule. In sum, the results thus far indicate that, at least for the pretraining levels employed in the present study, rule effects are not eliminated through AI training.

In agreement with previous research (e.g., Bourne & Guy, 1968a), truth table was found to be significant, $F(3,90) = 3.14$, $p < .04$. Error means for each truth table class are 1.34(TT), 2.33(TF), 1.53(FT), and 2.83(FF). These data were further analyzed by means of Tukey HSD tests, which revealed that the TT class was significantly easier than both the TF ($p < .05$) and the FF ($p < .01$). The FT class, in addition, was easier than the FF ($p < .01$).

Truth table also interacted with rule, $F(3,90) = 3.12$, $p < .04$. Table 7 presents the error means associated with this interaction. The most difficult class for the Dj rule is the FF, while the most difficult class for the Cd is the TF. In both cases, the most difficult truth table class was that which must be assigned to the negative response category. Apparently, *S*s focus on and attain more easily those truth table classes which are

TABLE 7

ERROR MEANS FOR THE INTERACTION OF TRUTH TABLE AND RULE

Rules	Truth Table Classes TT	TF	FT	FF
Dj	.39	.72	1.33	3.22
Cd	2.28	3.94	1.72	2.50

assigned to tne positive response category. No further effects were obtained in the final problem analysis.

Successive Problem Analyses

Data were further analyzed by means of two repeated measures analyses on successive AI problems. First, the data of all Ss receiving five AI problems was pooled. This analysis included data from those Ss in the four pretraining problems condition, as well as data from the first five problems given the eight pretraining problems condition Ss. In addition, performance over nine AI problems was assessed, utilizing only the data of those Ss in the eight pretraining problems condition.

Five Successive AI Problems

A 2(rules) x 4(truth table classes) x 5(problems) repeated measures analysis of variance was performed on errors. The effects of rule, truth table, and the interaction of these variables were as previously reported. Rules varied reliably, $F(1,22) = 6.24$, $p < .02$. Error means were 2.02(Dj) and 3.69(Cd), again reflecting the overall ease of the Dj compared to the Cd rule. Truth table also reached significance, $F(3,66) = 4.75$, $p < .01$. Means for each truth table class are 1.70, 3.14, 1.67, and 3.21, for the TT, TF, and FF respectively. Tukey HSD analyses performed on this data revealed the FT to be easier than the TF or FF, while the TT was easier than the FF only. Furthermore, the interaction of rule and truth table also attained significance, $F(3,66) = 8.04$, $p < .001$. Table 8 presents the error means for this interaction. In keeping with previously described findings, it can be seen that these effects primarily reflect the greater difficulty of the truth table class which is assigned to the negative category (FF for the Dj; TF for the Cd).

Finally, the main effect of problems reached significance, $F(4,88) = 3.10$, $p < .04$.

TABLE 8

ERROR MEANS FOR THE INTERACTION OF RULE AND TRUTH TABLE

Rules	Truth Table Classes TT	TF	FT	FF
Dj	.60	2.09	1.73	3.07
Cd	3.34	5.12	2.79	3.55

Error means are 3.49, 2.82, 2.02, 2.61, and 1.04 for Problems 1 through 5 respectively. Trend analyses performed on these data revealed a significant linear trend ($p < .01$), indicating that each successive AI problem required fewer errors to reach solution. Apparently, Ss tend to benefit from each successive AI problem, due to such factors as warm-up, learning to learn, and the possible development of general or rule-specific AI strategies.

Nine Successive AI Problems

A 2(rules) x 4(truth table classes) x 9(problems) repeated measures analysis of variance was performed on errors to criterion. In agreement with previously reported effects, rule attained significance, $F(1,80) = 6.19$, $p < .03$. Error means were 1.48 and 3.44 for the Dj and Cd rules, respectively. The main effects of truth table, in contrast to previous analyses, did not reach significance, $F(3,30) = 3.38$, $p < .07$. However, the interaction of truth table and rule obtained significance, $F(3,30) = 5.58$, $p < .02$. Table 9 presents the error means associated with this effect. The most difficult truth table classes are again those which are assigned to the negative category. Further, it can be seen that the form of the truth table main effect, although nonsignificant, is similar to previously-reported truth table effects. No other effects reached significance in this analysis.

TABLE 9

ERROR MEANS FOR THE INTERACTION OF TRUTH TABLE AND RULE

Rule	Truth Table Classes TT	TF	FT	FF
Dj	.24	.92	1.22	3.55
Cd	2.92	2.67	2.19	3.00

IV
Discussion

The major prediction in the present study was that pretraining on several AI tasks involving the same underlying rule would reduce or eliminate rule effects in a subsequent AI task. As evidenced by the absence of a rule by pretraining interaction, the results show no clear effect of various levels of AI training in reduction of rule differences. Typical rule effects were present in transfer for both pretraining conditions.

The investigation of rule effects under conditions of RL and AI discussed earlier in this paper is particularly relevant to the focus of the present study, since the same relative rule difficulty has been found (e.g., Haygood & Bourne, 1965) in both tasks. Several possibilities as to the cause, or causes, of such similarity in relative rule difficulty can be identified. Other work (Ingison, in preparation) has shown that relative rule differences in RL and AI are probably not due to familiarity with the rule per se. The present results further suggest that such similarities are not due to practice on AI problems involving the same rule, at least for the pretraining levels utilized in the present experiment. The question still remains as to the possible nature of the one or more critical factors involved in AI rule effects.

One possibility is that still more rule-specific AI training is needed in order to effect a reduction of rule differences in AI. It is possible that overtraining to a high degree may be necessary to effect a reduction in relative rule differences in AI tasks through the development of rule-specific AI strategies. A second possibility is that *S* must possess a certain repertoire of skills—a repertoire which may include rule familiarization in RL or AI—in order to eliminate rule differences in AI. There are several variations of such composite skills which may provide the key to reducing rule differences in AI. One possibility is to instruct or train *S* about the truth table in addition to rule familiarization in either RL or AI or both. It is possible that attainment of solution in AI tasks requires a facility with truth table coding in order to reduce relative rule effects. Knowledge of the truth table as well as the rule may be valuable in AI, as it is possible that knowledge of the exact pattern types placed in each response category will facilitate identification of the relevant attributes, especially for the more difficult rules.

To illustrate, *Ss* may be highly trained on one rule and yet relatively naive about the truth table classes, as in a two-category problem no clear distinction between the classes placed in the same response category is required. Thus, *Ss* can solve the problem by clearly defining one response category and placing all other patterns (by elimination) in the second category. For example, the Cj might be expressed thus: if both attributes are present, it is positive; all other patterns are negative. Truth table trained *Ss*, on the other hand, should have a more developed knowledge of the differences among individual classes contained in each response category. The Cj might be expressed in this way: if both attributes are present, it is positive; if only the first attribute, the second attribute, or neither is present, it is negative. On this basis, certain performance differences between truth table naive and truth table sophisticated *Ss* might be expected in AI tasks. Naive *Ss* might be able to gain information effectively from only one response category (the smallest or best defined category). Due to the undifferentiated nature of the classes in the second response category, *Ss* may gain little information about the relevant attributes from these instances. Armed with a better developed idea of the classes of stimuli in each response category, sophisticated *Ss* are in a better position to gain information efficiently from both the positive and negative categories in an AI task.

Such differences in the capability of utilizing information from both response categories would be especially important for more difficult (e.g., Cd) rules. The Cd rule requires utilization of information from both response categories for efficient identification of attributes. In the Cd rule, the negative category may be the most efficient source of information about the first relevant attribute, since all TF's have this attribute in common, but the positive category must also be searched for the second attribute. As efficient use of both categories may be helpful in solving AI problems involving this rule, truth table sophisticated *S*s might be expected to solve more quickly. Few, if any, differences in the performance of truth table naive and truth table sophisticated *S*s would be expected for the Dj rule, as this rule depends less on information gained from *both* response categories—that is, the Dj would probably be solved by both groups by a strategy of comparing the TT's, TF's, and FT's to each other to identify the invariant relevant attributes. The exact nature of such composite skills and the effect such skills may have on relative rule difficulty in AI remain to be determined in further studies.

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GPO 805-879-2

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