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The Effects of Truth Table Pretraining and Intradimensional Variability on Rule Learning and Attribute Identification Tasks

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THE EFFECTS OF TRUTH TABLE PRETRAINING AND INTRADIMENSIONAL VARIABILITY ON RULE LEARNING AND ATTRIBUTE IDENTIFICATION TASKS

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_S_s were required to sort geometrical patterns into positive or negative instances. According to (_a_) an attribute identification problem (wherein one of three conceptual rules was given: Disjunctive, Conditional, or Biconditional) or (_b_) Rule learning problem (wherein the two relevant attributes were given: either yellow, triangle or blue, circle). Intradimensional variability for each condition was either five, seven, or nine levels.

The Rule effect was the only significant source of variance even though performance did worsen as intradimensional variability was increased.

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Chapter I

INTRODUCTION

In human conceptual behavior, a concept is formed when two or more objects can be grouped together because of some common feature that they share. In concept learning tasks that have two choices, one categorizes all stimuli of a problem together as either being examples or non-examples of a particular concept. In experimental psychology, the relevant feature or features of the concept are determined by the experimenter and the subject is confronted with the task of discovering them. Human conceptual ability is a learned process and enables man to pay attention to the relevant characteristics and ignore the irrelevant characteristics of his environment, especially when he is engaged in some type of problem solving activity. Concept learning is of interest to the behavioral scientist because of the relevance to learning processes, cognitive processes, and goal-directed behavior in humans.

A typical population of stimuli in concept learning tasks would be defined by a number of dimensions which are subdivided into a number of attributes. For example, a problem that had two dimensions (form and color) each with three attributes (square, circle, triangle, and red, yellow, and blue, respectively) would entail a total number of nine unique patterns in the population. If the color "blue" were arbitrarily chosen as the relevant attribute, blue objects may be considered as examples of the concept, while objects which are _not_ blue would be non-examples. To sort stimuli and solve conceptual problems, all objects may be classified as being positive or negative instances (examples vs. non-examples) of the concept. Informative feedback presented to _S_ is required to confirm correct choices and negate incorrect ones.

A unidimensional problem is one in which only a single relevant dimension, i.e. color, is required to solve the problem. In a bidimensional problem, _S_s are required to discover one attribute from each of two dimensions in order to solve the problem. For example, "yellow, triangle" might be chosen by the experimenter (_E_) as the relevant attributes of color and form. All other forms and colors are not relevant for the solution.

According to Haygood and Bourne (1965), attribute identification (AI) requires _S_s to determine unknown attributes of a stimulus population in which the rule specifying the relationship between attributes is known, while rule learning (RL) requires _S_s to determine the rule describing the relationship between known (given) attributes. The present study will be concerned with both _AI_ and _RL_ aspects of conceptual behavior and only bidimensional problems will be considered.

The 1965 study of Haygood and Bourne employed different bidimensional rules. Even though the two relevant attributes remained the same, a different classification scheme of positive and negative instances was dictated by the use of a particular rule. Four primary bidimensional rules were used by Haygood and Bourne. If one relevant attribute was _x_ and the other _y_, the four rules and their appropriate verbal descriptions for the specification of the concepts would be: Conjunctive (Cj)--(_x_ and _y_); Disjunctive (Dj)--(_x_ and/or _y_); Conditional (Cd)--(if _x_ then _y_); and Biconditional (Bd)--(_x_ if and only if _y_). Table 1 illustrates the stimulus assignments according to the four rules when three attributes within three dimensions are used. The proportion of positive and negative instances varies according to the conceptual rule being applied.

The Haygood and Bourne (1965) data indicated that certain _S_s intuitively used a type of stimulus coding

TABLE 1

ASSIGNMENT OF STIMULUS CLASSES TO RESPONSE CATEGORIES

(+ and -) FOR FOUR PRIMARY RULES

Stimulus Class	General Notation	Stimulus Set	Rules			
			Cj	Dj	Cd	Bd
YTr	TT	YTr	+	+	+	+
YTr	TF	YS,YC	-	+	-	-
YTr	FT	RTr,BTr	-	+	+	-
YTr	FF	RS,BS RC,BC	-	-	+	+

The following abbreviations are used: T=true (or present); F=false (or absent); R=red; Y=yellow; B=blue; S=square; Tr=triangle; C=circle.

which collapses the entire stimulus population according to whether relevant attributes are present (T) or absent (F). The four resulting stimulus classes include patterns embodying both (TT), the first but not the second (TF), the second but not the first (FT), and neither (FF) relevant attributes. In the RL problems, S learned to assign these four classes to two categories, positive and negative instances of the concept. This strategy converted RL problems into an almost trivial 4:2 paired associate task.

In a study by Haygood and Kiehlbach (1965), a "Truth Table" pretraining strategy was introduced in an attempt to minimize the difficulty of RL problems. A higher level of performance was reached by Ss who received pretraining on the truth table strategy relative to Ss who received no such pretraining. Prior to the experiment proper, the pretraining group sorted patterns into four stimulus classes according to whether the relevant attributes were present or absent. An example of this classification is presented in Figure 1.

A recent study by Guy (1969) used the truth table pretraining procedure for both children and adults and equalized the degree of difficulty between conceptual rules. Truth table pretraining apparently reduced the difficulty

	Δ	$\overline{\Delta}$
Y	TT	TF
$\overline{Y}$	FT	FF

Figure 1. Truth table using relevant attributes of yellow triangle Y=yellow Δ = triangle; $\overline{\Delta}$ =not triangle; $\overline{Y}$=not yellow.

of learning certain rules. A consistent ordering of rule difficulty from easiest to most difficult is Cj, Dj, Cd, Bd. The same ordering was reported by Haygood and Bourne (1965), Bourne and Guy (1968a), and Vodarski (1970). The Cj and Dj rules are probably more familiar to _S_s in everyday life and are therefore easier to use than Cd and Bd rules.

Since some rules only have a few negative instances, it would seem beneficial for _S_s to sort out negative instances from positive instances to develop a "negative focusing strategy" in certain RL tasks. A study by Bourne and Guy (1968b) revealed that _S_s attained a higher level of performance on RL tasks when trained on a given mixture of positive and negative instances rather than training on _only_ positive or _only_ negative instances. In a study by Haygood, Harbert, and Omlor (1970), there was an increase in intradimensional variability by using two, four, and six attributes per dimension in a concept identification experiment. In this study, _S_s were required to sort sets of alphabetical letters, and as the number of attributes per dimension increased, the _S_s' performance improved. This effect was attributed to the increased saliency effect of making the positive category more obvious to the _S_s. In a recent study by Vodarski (1970), intradimensional levels of four and five attributes per dimension were used, thus varying the ratio of positive and negative instances for consideration by Ss. As a result of the increases in intradimensional variability, the rules became progressively more difficult for Ss. One explanation could be that Ss lacked any experience with the Cd and Bd rules. Hunt (1962) has stated that some principles are more directly generated from "natural" strategies than others.

Vodarski (1970) employed four and five attributes per dimension and it was shown that Ss seemed to follow an ordering of rule difficulty consistent with earlier research. Increasing the number of attributes per dimension tended to retard the level of performance by Ss regardless of the rule. The present study was similar to the study conducted by Vodarski (1970), but with the addition of truth table pretraining procedure for Ss and an expansion of the intradimensional variability to five, seven, and nine attributes per dimension. Also, Attribute Identification performance was compared to Rule Learning performance.

In a study by Bourne and Guy (1968b) the Cd rule yielded equal levels of performance with AI and RL Ss. The present study tested the reliability of that outcome when additional levels of a dimension were added to the problem. The smaller and more homogeneous instance, either positive or negative, should have an effect on the AI performance but may not have influenced RL performance. The present experiment also was designed to test the reliability of the difficulty ordering between the different conceptual rules for both AI and RL.

Chapter II

METHOD

Subjects and Design

The Ss were 72 Central Washington State College students who volunteered for participation in psychology experiments. The Ss were randomly assigned to 36 basic conditions in a 2 X 2 X 3 X 3 factorial design as illustrated in Figure 2. The factors were (a) Rule learning and attribute identification problems, (b) Relevant attributes of yellow, triangle and blue, circle (c) Three separate rules (Dj, Cd, and Bd), and (d) Three intradimensional levels (five, seven, and nine).

Materials and Apparatus

The stimuli were geometric patterns that varied along two dimensions of color and form in either five, seven, or nine attributes per dimension. Table 2 illustrates the proportion of positive and negative instances according to the particular rule and number of intradimensional levels. In the five level condition, attributes were yellow, red, blue, green, and black in forms of circles, stars, squares,

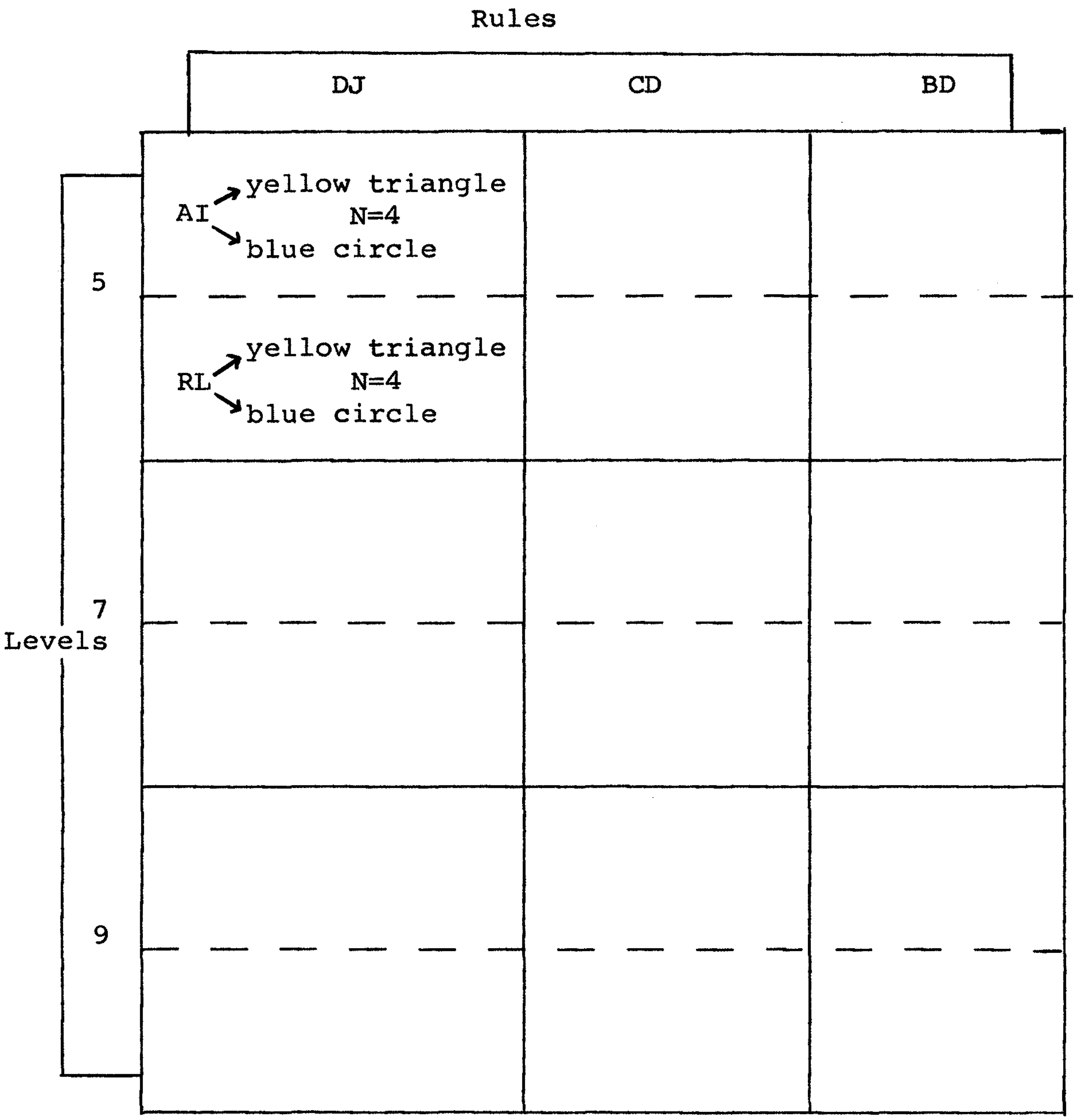

Figure 2. A 2 X 2 X 3 X 3 Factorial design using attributes of yellow triangle and blue circle.

TABLE 2

ASSIGNMENT OF POSITIVE AND NEGATIVE INSTANCES BY TRUTH TABLE CLASSES WITHIN RULE CONDITIONS USING THE RELEVANT ATTRIBUTES ATTRIBUTE PRESENT =T; ATTRIBUTE ABSENT =F

LEVELS	5 LEVELS			7 LEVELS			9 LEVELS		
Bidimensional Rules	DJ	CD	BD	DJ	CD	BD	DJ	CD	BD
Both present attributes (TT)	+	+	+	+	+	+	+	+	+
Number of patterns in class	1	1	1	1	1	1	1	1	1
The first but not the second attribute (TF)	+	-	-	+	-	-	+	-	-
Number of patterns in class	4	4	4	6	6	6	8	8	8
The second but not the first attribute (FT)	+	+	-	+	+	-	+	+	-
Number of patterns in class	4	4	4	6	6	6	8	8	8
Neither relevant attribute (FF)	-	+	+	-	+	+	-	+	+
Number of patterns in class	16	16	16	36	36	36	64	64	64
Number of Positive Instances	9	21	17	13	43	37	17	73	65
Number of Negative Instances	16	4	8	36	6	12	64	8	16
Total number of unique patterns	25			49			81		

COLORS		FORMS
Yellow	- - - Two relevant attributes - - -	Triangle
Blue		Circle
Red	5 Levels	Square
Brown		Hexagon
Green		Star
Purple		Crescent
Gray	7 Levels	Cross
Pink		Rectangle
Orange	9 Levels	Diamond

hexagons, and triangles. The seven level condition contained all the forms and colors of the five level condition with the added colors of violet and gray in forms of crosses and crescents. The nine level condition contained all colors and forms of level seven with the additional colors of pink and orange and the additional forms of diamonds and rectangles.

The geometrical patterns were prepared on 4 x 6 inch cards, photographed, and individually mounted on 2 x 2 inch slides for individual presentation on a translucent viewing screen by a Kodak Carousel Projector. Prior to the actual presentation of the problem, Ss were presented with five, seven, or nine example slides to insure that colors and forms were easily distinguishable.

Eighty patterns were arranged in a slide tray for presentation to Ss. The order was predetermined so that every four trials randomly presented one each of the TT, TF, FT, and FF class. Some attributes appeared more than others since the Truth Table Classes appeared with equal frequency according to the specifications of each truth table class. The 80 slides were repeated until S met the criterion of 16 correct, consecutive responses. If Ss were unable to meet criterion after an hour on the task, they were considered non-solvers.

The Ss responded by pressing one of two buttons labeled "Yes" or "No" on a response panel located below the viewing screen. Responses were recorded automatically by a Lehigh-Valley tape punch and after each response, S was given immediate feedback by the illumination of a small bulb over the correct choice. The feedback length and intertrial interval, which were a combined length of two seconds, were controlled automatically by Lehigh-Valley electronic equipment. When a response (button press) was made by S, the equipment automatically removed the slide and selected the next slide for presentation. Pre-punched tapes (which advanced automatically to the appropriate stimulus) provided feedback to S and were prepared from a Lehigh-Valley forward tape reader (Vodarski, 1970).

Task and Procedure

All Ss received pretraining prior to the presentation of stimuli, in which they were required to sort 45 cards into a 2 x 2 truth table matrix (presented in Figure 3) utilizing the relevant attributes of red, square. Pretraining cards were geometric patterns (squares, circles, and triangles) mounted on 3 x 5 cards. The patterns were five cards of each of the following colors: red, blue, yellow. After correctly sorting the cards, Ss were asked to sit before the viewing screen.

	SQUARE	NOT SQUARE
RED	TT	TF
NOT RED	FT	FF

Figure 3. Truth Table Pretraining Matrix Using Relevant Attributes of Red Square.

Separate instructions were given to each S, depending on whether they received a rule learning or attribute identification problem (see Appendix A). For rule learning conditions, S was presented with a card with two relevant attributes, e.g., yellow, triangle, or blue, circle. The S was then told by E that he must discover the relationship between the two given attributes. The Ss pressed the "Yes" button if the pattern was an example of the concept and the "No" button if the pattern was not an example of the concept.

Attribute identification Ss were presented with a Venn diagram card (see Appendix A) according to the Dj, Cd, or Bd rule to which they were assigned. The AI Ss were then told by E that they must discover the attributes relating the characteristics (or rule). The Ss were also told to press the "Yes" button if the pattern was an example of the concept and the "No" button if the pattern was not an example of the concept.

Chapter III

RESULTS

Analyses of variance were calculated on (_a_) the number of errors to criterion, and (_b_) the number of trials to criterion for each _S_ (see Appendix B for raw data).

Errors to Criterion. Figures 4 and 5 illustrate the mean number of errors to criterion for all groups in the attribute identification and rule learning problems, respectively. The results of an analysis of variance (see Table 3) performed on the data did not approach statistical significance ($p > .05$) for Rules, Problems, Levels, Attributes or any of the interactions. A second analysis of variance performed on the data (see Table 4) collapsing the Attribute effect was also statistically insignificant ($p > .05$) for Rules, Problems, Levels, and all other interactions. A t test comparing mean number of errors for five and nine levels in the attribute identification condition only was also not statistically significant ($t = .78$, df = 6, $p > .05$).

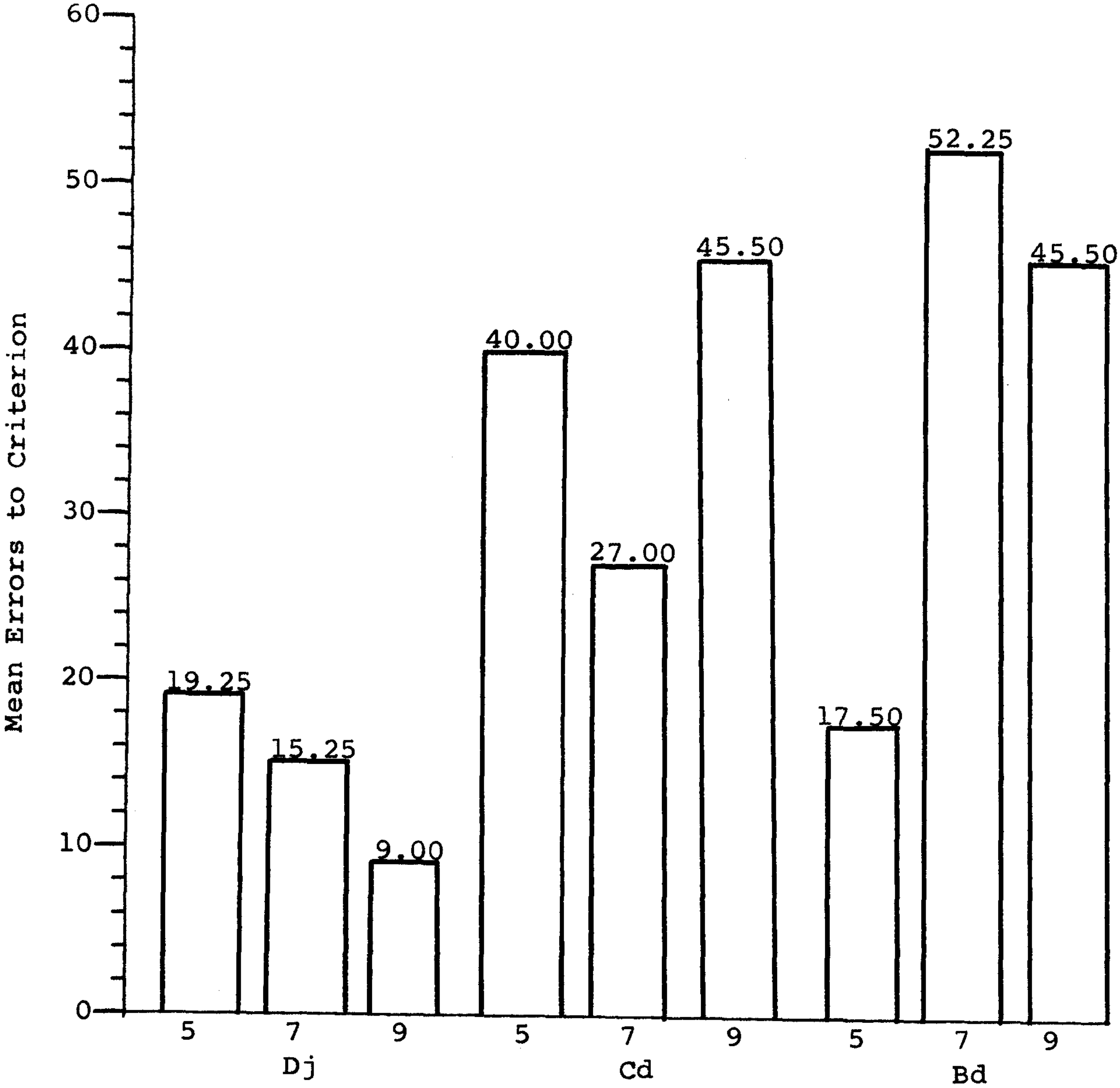

Figure 4. Mean errors to criterion for attribute identification problems based on five, seven and nine attributes per dimension for the Dj, Cd, and Bd rules.

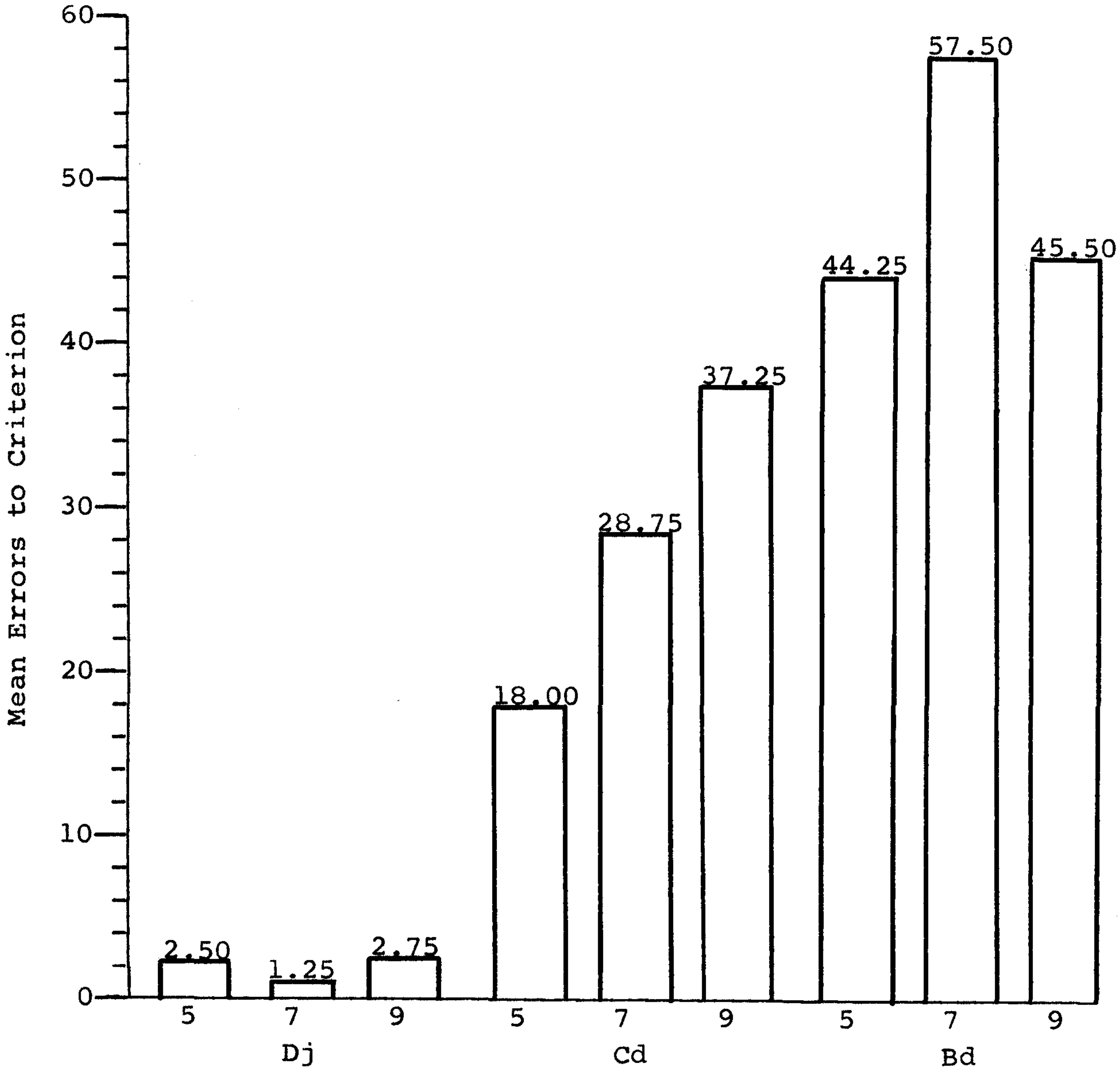

Figure 5. Mean errors to criterion for rule learning problems based on five, seven, and nine attributes per dimension for the Dj, Cd, and Bd rules.

TABLE 3

SOURCE TABLE FOR THE ANALYSIS OF VARIANCE

FOR ERRORS TO CRITERION

Source	df	MS	F
A (Rules)	2	839.54	1.14
B (AI/RL)	1	300.13	.41
C (Levels)	2	435.38	.59
D (Attributes)	1	74.01	.10
A x B	2	852.54	1.16
A x C	4	631.85	.86
A x D	2	166.02	.23
B x C	2	19.29	.03
B x D	1	48.35	.07
C x D	2	140.51	.19
A x B x C	4	401.27	.55
A x B x D	2	78.01	.11
A x C x D	4	187.33	.26
B x C x D	2	181.26	.25
A x B x C x D	4	204.24	.28
Error Term	36	734.10	

TABLE 4

SOURCE TABLE FOR THE ANALYSIS OF VARIANCE

WITH COLLAPSED ATTRIBUTE EFFECT FOR ERRORS TO CRITERION

Source	df	MS	F
A (Rules)	2	16179.08	.96
B (AI/RL)	1	600.25	.36
C (Levels)	2	870.75	.52
A x B	2	1705.08	1.02
A x C	4	1263.71	.75
B x C	2	38.58	.02
A x B x C	4	802.54	.48
Error Term	18	1677.36	

Trials to Criterion. The mean number of trials for all groups in the attribute identification and rule learning conditions are illustrated in Figures 6 and 7. An analysis of variance performed on the data revealed a significant Rule effect ($F = 10.76$, $p < .01$), although statistical significance was not achieved for Problems, Levels, Attributes, or other interactions (see Table 5). An analysis of variance (see Table 6) collapsing the Attribute condition also produced a significant rule effect ($F = 11.26$, $p < .01$), but statistical reliability was not obtained for the other interactions.

A multiple comparisons test (Tukey's HSD) was performed comparing the means of the three rules (see Table 7). Results of the multiple comparisons test revealed significant differences in both the Conditional rule (HSD = 65.21, $p < .05$) and the Biconditional rule (HSD = 83.15, $p < .01$). A t test comparing five and nine level means in the attribute identification condition did not approach any level of significance ($t = 1.10$, df = 6, $p > .05$).

Inspection of Figures 5 and 7 for Trials and Errors to criterion indicated that the traditional ordering of difficulty between the three rules was obtained for the rule learning condition. The most pronounced performance

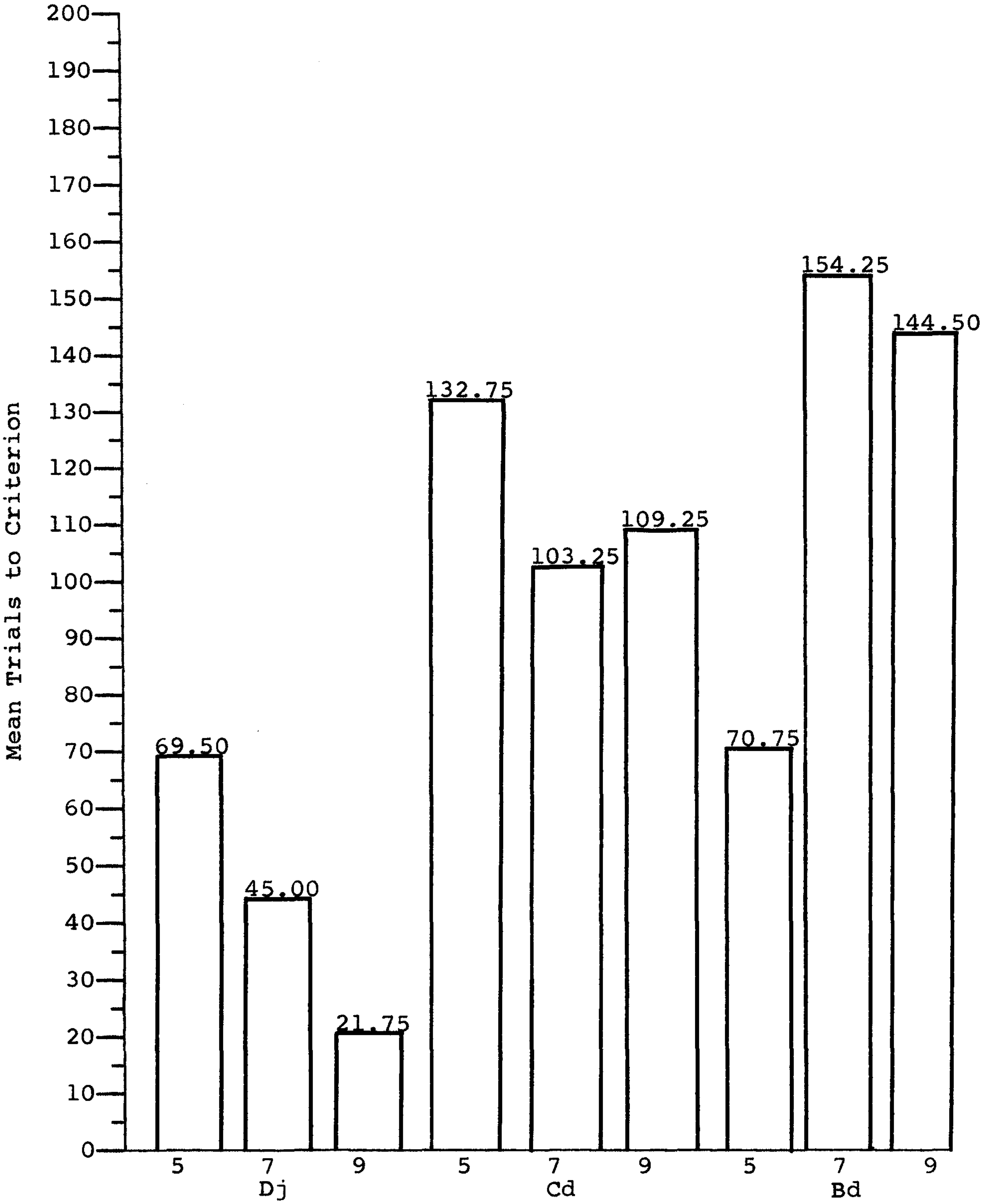

Figure 6. Mean trials to criterion for attribute identification problems based on five, seven, and nine attributes per dimension for the Dj, Cd, and Bd rules.

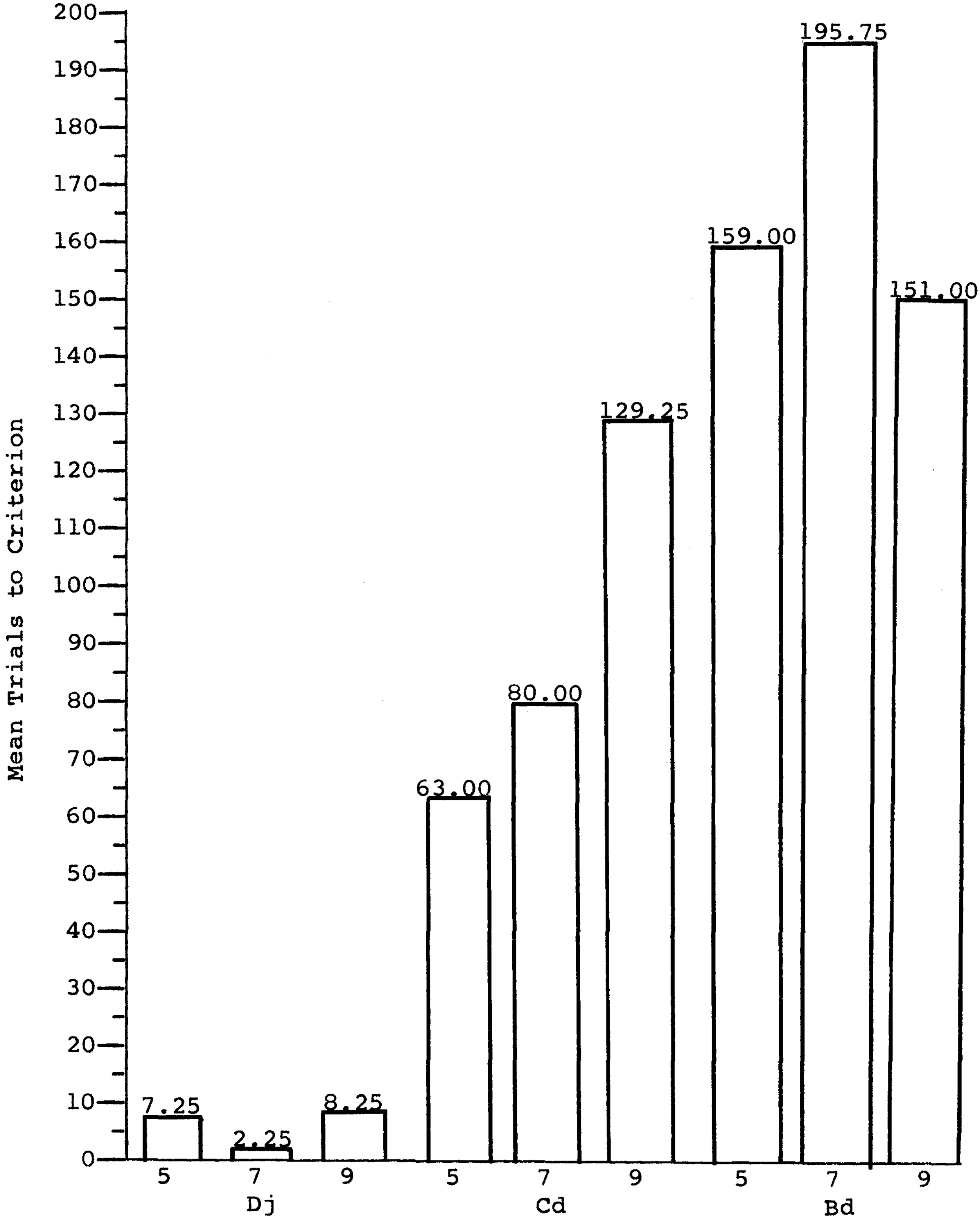

Figure 7. Mean trials to criterion for rule learning problems based on five, seven, and nine attributes per dimension for the Dj, Cd, and Bd rules.

TABLE 5

SOURCE TABLE FOR THE ANALYSIS OF
VARIANCE FOR TRIALS TO CRITERION

Source	df	MS	F
A (Rules)	2	90145.43	10.76*
B (AI/RL)	1	806.68	.10
C (Levels)	2	1190.10	.14
D (Attributes)	1	6.13	.00
A x B	2	11795.93	1.41
A x C	4	4455.89	.53
A x D	2	3159.54	.38
B x C	2	456.10	.05
B x D	1	4155.68	.50
C x D	2	780.79	.09
A x B x C	4	4273.85	.51
A x B x D	2	1913.43	.23
A x C x D	4	7038.58	.84
B x C x D	2	3222.35	.39
A x B x C x D	4	4450.35	.53
Error Term	36	8378.68	

*$p < .01$

TABLE 6

SOURCE TABLE FOR THE ANALYSIS OF VARIANCE WITH COLLAPSED ATTRIBUTE EFFECT FOR TRIALS TO CRITERION

Source	df	MS	F
A (Rules)	2	180290.86	11.26*
B (AI/RL)	1	1613.35	.10
C (Levels)	2	2380.19	.15
A x B	2	23591.86	1.47
A x C	4	8911.78	.56
B x C	2	912.20	.06
A x B x C	4	8547.69	.53
Error Term	18	16005.86	

*$p < .01$

TABLE 7

MULTIPLE COMPARISONS TEST (TUKEY'S HSD) PERFORMED

FOR MEAN RULES FOR TRIALS TO CRITERION

Rule	DJ 25.67	CD 102.92	BD 146.71
DJ 25.67	-	77.25*	121.04**
CD 102.92	-	-	43.79
BD 146.71	-	-	-

* $< .05$
** $< .01$

difficulty occurred in the Conditional and Biconditional rules which was consistent with earlier research by Vodarski (1970). As the number of intradimensional levels increased, problem difficulty increased with the exception of the Ss in the nine level Biconditional rule problem who reached a higher level of performance than those in the seven level condition. This was not statistically reliable.

By comparison, Figures 4 and 6 Trials and Errors to Criterion in the attribute identification condition indicate that performance was much less consistent than for rule learning. Fewer trials and errors to criterion were made by Ss in rule learning conditions in the Dj and Cd rules relative to the attribute identification conditions. This trend was reversed for the Bd rule wherein the AI conditions reached a higher level of performance than for the RL condition. Further, an increase in intradimensional levels seemed to reduce the difficulty for the Dj rule AI for both trials and errors to criterion. The present results are unclear concerning the effect of increasing the number of levels for AI on the Cd and Bd rules. The seven level rule performance on AI was slightly higher than the five level but this trend was reversed for the Bd rule. The nine and seven levels for both Cd and Bd in AI did not appear to be noticeably different.

Chapter IV

DISCUSSION

The present experiment compared performance differences on the learning of three bidimensional rules (Dj, Cd, Bd) with either five, seven or nine attributes for both rule learning and attribute identification. As speculated by Vodarski (1970), a change in the number of attribute levels for certain rules could enable Ss to utilize a negative focusing strategy (attention to negative instances) rather than a positive focusing strategy (attention to positive instances). This is plausible because the ratio of positive to negative instances changes markedly as the number of intradimensional levels increase. Therefore, the Cd rule would have few negative instances for Ss to consider compared to the number of positive instances as the number of levels increase. Theoretically, if Ss could adopt a negative focusing strategy for certain rules, the traditional ordering of rule difficulty may not be obtained. This possibility exists more for the RL condition than for the AI condition simply because the attributes are known in the former condition and the RL problem lends itself more to a truth table type of classification in conceptual behavior.

Haygood, Harbert and Omlor (1970) found that performance improved on a task of sorting sets of alphabetical letters when intradimensional variability was increased using the affirmative (Af) and conjunctive (Cj) rules. The RL results of the present experiment are consistent with the results of the research by Vodarski (1970), in that the same ordering of rule difficulty was obtained. However, the present results do offer some contradiction to the research of Haygood et. al. (1970), but the experimental method in the present experiment was quite different. According to the RL performance plotted on Figures 5 and 7 Ss achieved a higher performance on the Dj rule, an intermediate performance on the Cd rule, and the lowest level of performance on the Bd rule. It would appear that an increase in the number of attributes did not facilitate RL performance. However, Figures 4 and 6 indicate that rule difficulty appears to have been reduced for seven levels compared to five levels in the Cd rule for AI and five levels in the Bd rule compared to five levels in the Cd rule. This outcome is difficult to explain. It appears that an intra-dimensional level increase in AI causes more variability than in RL.

The inverse ordering of rule difficulty seen in Figures 4 and 6 for the Dj rule for Ss in the AI condition suggests that the performance level improves as the number of attribute levels increase. This result seems contrary to what one might expect since Ss appeared to learn more easily as total number of patterns increases.

Haygood and Bourne (1965) revealed that certain Ss collapsed an entire stimulus population into the four (TT, TF, FT, and FF) classes in RL behavior. The Haygood and Bourne data revealed the ordering of rule difficulty which has been maintained in research by Bourne and Guy (1968), Vodarski (1970), and the RL condition of the present study.

Research by Haygood and Kiehlbach (1965) introduced a "Truth Table" pretraining strategy (see Table 3), in which a higher level of performance was obtained by Ss receiving pretraining as compared to Ss receiving no such pretraining. In a recent study by Guy (1969), rule difficulty was equalized through the use of the truth table pretraining procedure for adults and children. The truth table pretraining procedure used for all Ss in the present experiment was intended to insure relatively equal ability in the learning of tasks by Ss.

It would appear that most Ss adopted a positive focusing strategy in learning the present conceptual tasks. Since Ss would have more everyday experience with the Dj rule it should be easier than either of the other two. However, the increase in attribute levels for AI in this rule seemed to reduce difficulty rather than increase it. More examples for each S to sort should have further compounded rule difficulty. Negative focusing could have accounted for the improved performance on the seven level Cd problem relative to the five level Cd problem but this difference was not statistically significant.

Vodarski (1970) increased intradimensional variability from four to five levels, utilizing the Dj, Cd, and Bd rules. The data revealed that performance worsened with increased intradimensional variability. The RL results of the present study revealed results similar to Vodarski's (1970) research in that performance worsened with increased intradimensional variability from five, seven, and nine levels. Only the nine level condition for the Bd rule was inconsistent since it showed a better performance level than the seven attribute condition. In the present study, the only significant effect was for rules (see Tables 5 and 6), and a Tukey's HSD multiple means comparison test, performed across rules, revealed a significant difference in the Cd rule and the most pronounced difference occurred in the Bd rule. None of the other _t_ tests or analyses of variance performed on the data revealed reliable differences. In examining Figures 4 through 7 it would appear that the additional attribute levels produced a noticeable decrement in the performance of most of the conditions.

All _S_s were allowed an unlimited number of trials in one hour and, if criterion was not met within one hour, _S_ was considered a non-solver. On some of the more difficult problems, fatigue and frustration seemed evident, and one _S_ was removed from the data, since hapazard responses were being made.

Increasing intradimensional variability seemed to produce a decrement in most of the performance in the present experiment. Subsequent studies could explore increased attributes even more but the dimension of color, according to a pilot study, does not lend itself to discriminable attributes among _S_s beyond nine levels. Other dimensions, with more discriminability, e.g., number and alphabetical letter, could be studied to test the validity of the present results.

It is most unusual not to find a reliable difference between AI and RL. Attribute identification was more difficult for Dj in AI relative to RL but this was not a consistent finding for the other two rules, especially the Bd. Additional studies designed to explore the effects of increasing the attributes in both AI and RL may help to illuminate some of the complex outcomes of the present experiment.

Chapter V

SUMMARY

The present study investigated the effects of intradimensional variability on bidimensional rule learning and attribute identification problems after truth table pretraining was given to *S*s.

Seventy-two *S*s were required to sort geometrical patterns into positive or negative instances. For half of the *S*s the task consisted of finding an unknown rule while the attributes were known (Rule Learning), and the other half of the *S*s were required to discover the attributes relating a given rule (Attribute Identification). All *S*s were randomly assigned to one of the three following rules: Disjunctive (Dj), Conditional (Cd), and Biconditional (Bd); five, seven or nine attribute levels; and, one of two problems with relevant attributes (yellow, triangle or blue, circle).

It was hypothesized that an increase in the number of attributes (intradimensional variability) could affect performance levels in the traditional difficulty ordering of the three rules (i.e., Dj, Cd, Bd, respectively) utilized in this research. Truth table pretraining was given to all Ss to insure that relatively equal problem solving abilities would obtain. Since the Cd rule has only a few negative instances relative to positive instances a negative focusing strategy by Ss could minimize the rule difficulty and facilitate the conceptual problem, especially in RL.

However, the results of the present study suggest that Ss utilized a positive focusing strategy. Increased intradimensional variability appears to have concomitantly increased the difficulty of the RL problems. Moreover, the traditional difficulty ordering was maintained in RL. The only exception was that the nine attribute Bd condition reached a higher level of performance than the seven attribute Bd condition.

For AI conditions the outcome was much more difficult to interpret. As the number of attributes increased for the Dj rule the performance levels also increased. This finding was not evident among the other rules, however, since no consistent trends in performance were obtained. Suggestions were made to further explore the effects of intradimensional variability on conceptual problems.

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APPENDIX A

APPENDIX A

INSTRUCTIONS (RL)

This is an experiment in concept learning. When solving a concept learning task, you learn to place objects in different categories because they share common characteristics. Placing all red objects in one category and all objects which are not red in a separate category is an example of solving a simple concept. Other concepts may have two or more features which are necessary for grouping. For example, we can take a deck of cards and sort them into four classes based on whether two important features are present or absent. (Pretrain Ss on 2 x 2 matrix)

A series of colored patterns will be presented to you on the viewing screen. You are to assign each pattern to the appropriate category by pressing either the "Yes" or the "No" button. Pressing the "Yes" button indicates that you think the pattern is an example of the concept; pressing the "No" button indicates that you think the pattern is not an example of the concept.

There are two important features for your problem and they are . . . (present card and verbalize, either "yellow, triangle", or "blue, circle"). You must discover the relationship between these two characteristics in order to classify the patterns into examples or non-examples of the concept. After you have pressed a button, a light will appear over one of the buttons to indicate the correct choice or the button you should have pressed.

When you have made your choice, press the button firmly and release it. You will begin by guessing. Do you have any questions? I will show you some of the patterns you will be seeing just to make sure that you can distinguish the colors (show trial slides). If you have any doubt about the color during the problem, simply ask. When you have 16 correct answers in a row, you have solved the problem.

INSTRUCTIONS (AI)

This is an experiment in concept learning. When solving a concept learning task, you learn to place objects in different categories because they share common characteristics. Placing all red objects in one category and all objects which are not red in a separate category is an example of solving a simple concept. Other concepts may have two or more features which are necessary for grouping. For example, we can take a deck of cards and sort them into four classes based on whether two important features are present or absent. (Pretrain _S_s on 2 x 2 matrix)

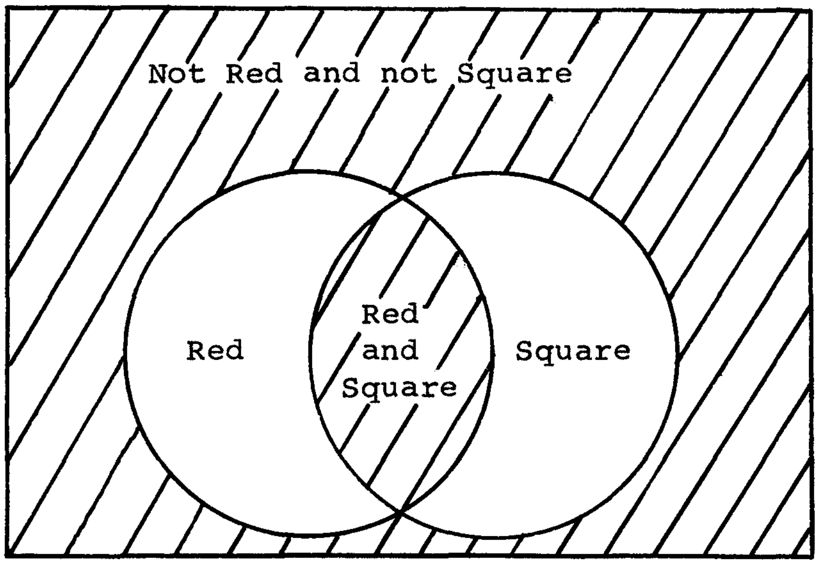
A series of colored patterns will be presented to you on the viewing screen. You are to assign each pattern to the appropriate category by pressing either the "Yes" or the "No" button. Pressing the "Yes" button indicates that you think the pattern is an example of the concept; pressing the "No" button indicates that you think the pattern is not an example of the concept.

There are two important features that you will be looking for. The rule that prescribes the relationship between the two characteristics is illustrated on this card (demonstrate proper Venn diagram card). Everything that is lined would be "Yes"; if unlined, "No" (using example of X = red, and Y = square). After you have pressed a button, a light will appear over one of the buttons to indicate the correct choice or the button you should have pressed.

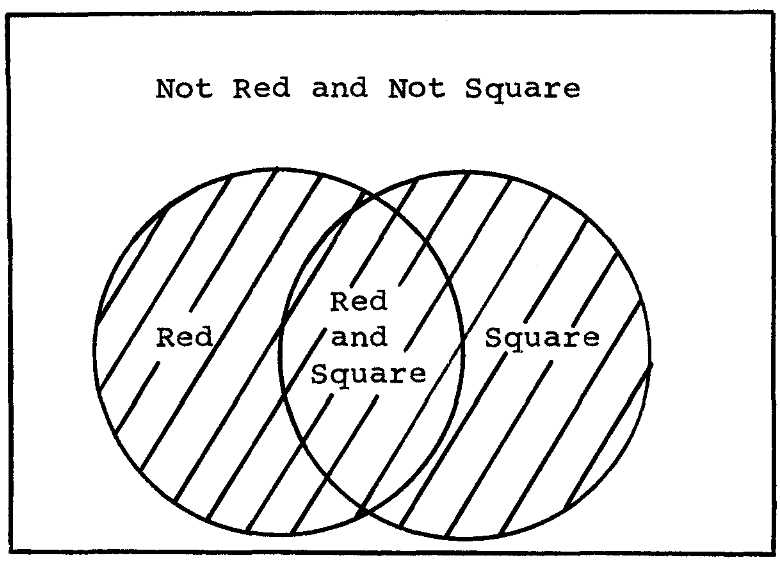
When you have made your choice, press the button firmly and release it. Do you have any questions? I will show you some of the patterns you will be seeing just to make sure you can distinguish the colors (show trial slides). If you have any doubt about the color during the problem, simply ask. When you have 16 correct responses in a row, you have solved the problem.

APPENDIX A

VENN DIAGRAMS GIVEN TO Ss IN AI CONDITIONS



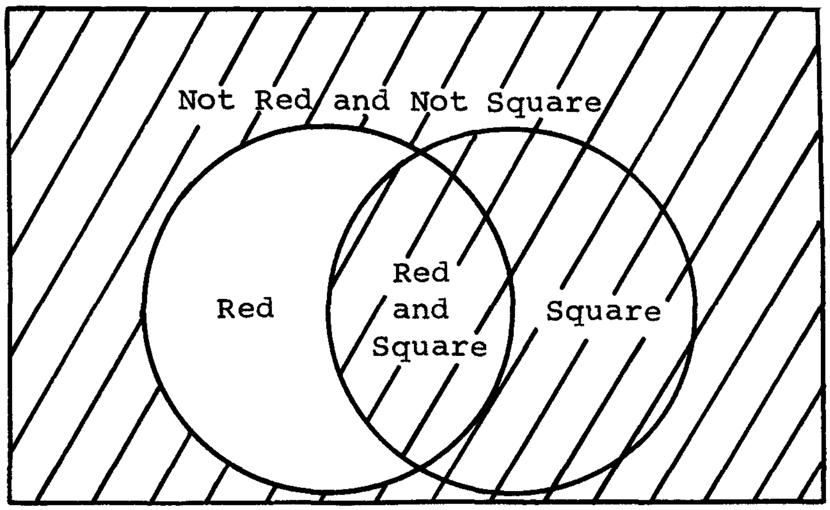
Biconditional: Red patterns are examples of the concept if and only if they are square.



Inclusive Disjunction: All patterns which are Red or Square or both are examples of the concept.

APPENDIX A

VENN DIAGRAMS GIVEN TO Ss IN AI CONDITIONS



Conditional: If a pattern is Red then it has to be square to be an example of the concept (but if it's not Red, it can be anything).

APPENDIX B

APPENDIX B

RAW DATA

AI = Attribute Identification
RL = Rule Learning
DJ = Disjunctive
CD = Conditional
BD = Biconditional
YT = Yellow Triangle
BC = Blue Circle

Subject	Condition	Rule	Level	Relevant Pattern	Trials	Errors
1	AI	DJ	7	BC	156	44
2	AI	BD	5	YT	67	22
3	RL	BD	5	YT	273	81
4	AI	BD	7	BC	202	81
5	RL	BD	7	BC	68	30
6	AI	DJ	7	YT	1	1
7	AI	BD	9	YT	196	76
8	AI	BD	9	BC	178	47
9	RL	DJ	5	BC	3	2
10	RL	DJ	7	BC	14	2
11	RL	CD	7	BC	97	40
12	RL	DJ	9	YT	0	0
13	AI	DJ	5	YT	188	55

Subject	Condition	Rule	Level	Relevant Pattern	Trials	Errors
14	AI	CD	5	YT	61	10
15	RL	CD	5	BC	13	5
16	RL	CD	9	BC	87	32
17	RL	CD	9	YT	99	36
18	RL	CD	7	YT	147	50
19	AI	CD	9	BC	167	88
20	AI	CD	9	YT	56	21
21	AI	CD	5	BC	136	52
22	AI	CD	7	YT	37	8
23	AI	BD	7	YT	69	32
24	AI	CD	9	YT	179	63
25	RL	BD	9	YT	13	8
26	RL	DJ	7	YT	3	2
27	RL	BD	7	YT	214	56
28	RL	DJ	5	YT	15	5
29	AI	CD	7	BC	69	23
30	RL	CD	5	YT	159	41
31	AI	DJ	5	BC	0	0
32	AI	DJ	9	BC	25	16
33	RL	BD	9	BC	29	9

Subject	Condition	Rule	Level	Relevant Pattern	Trials	Errors
34	RL	DJ	9	BC	23	6
35	AI	BD	5	BC	15	7
36	RL	BD	5	BC	140	45
37	AI	BD	9	BC	138	42
38	RL	CD	9	BC	293	69
39	RL	DJ	7	YT	0	0
40	RL	CD	7	BC	52	14
41	RL	BD	7	YT	265	57
42	AI	CD	7	BC	255	58
43	AI	CD	7	YT	52	19
44	RL	DJ	5	BC	0	0
45	AI	BD	5	YT	1	1
46	RL	DJ	7	BC	2	1
47	RL	CD	7	YT	24	11
48	RL	DJ	9	YT	6	2
49	RL	CD	9	YT	138	12
50	AI	DJ	7	YT	10	12
51	RL	BD	5	BC	59	10
52	AI	CD	5	BC	113	35
53	RL	BD	9	YT	382	87

Subject	Condition	Rule	Level	Relevant Pattern	Trials	Errors
54	AI	DJ	5	BC	80	20
55	RL	BD	5	BC	180	41
56	AI	DJ	5	YT	10	2
57	AI	DJ	9	YT	20	5
58	AI	DJ	7	BC	13	4
59	RL	BD	9	BC	180	78
60	AI	DJ	9	YT	22	13
61	RL	CD	5	YT	31	11
62	AI	CD	9	BC	35	10
63	RL	DJ	5	BC	11	3
64	AI	CD	5	YT	221	63
65	AI	BD	5	BC	206	40
66	AI	DJ	9	BC	20	2
67	RL	DJ	9	BC	4	3
68	AI	BD	9	YT	86	30
69	RL	CD	5	BC	49	15
70	AI	BD	7	YT	94	83
71	AI	BD	7	BC	52	13
72	RL	BD	7	BC	236	87