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Bidimensional Rule Difficulty and Problem Solving Strategy as a Function of Intelligence and Conceptual Task Type

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BIDIMENSIONAL RULE DIFFICULTY AND PROBLEM SOLVING STRATEGY AS A FUNCTION OF INTELLIGENCE AND CONCEPTUAL TASK TYPE

by

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VITA

The author, Donald Edward Raney, is the son of Edward C. Raney and Charlotte (Gibson) Raney. He was born on August 31, 1949 in New York, New York.

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ABSTRACT

Through use of an abbreviated form of the Wechsler Adult Intelligence Scale (WAIS), 48 subjects were assigned to either normal or superior IQ groups. With the constraint that equal numbers go to each group, subjects were then randomly assigned to either attribute identification (AI) or rule learning (RL) conceptual learning tasks. Using a reception paradigm, subjects solved bidimensional (two-valued) concepts for each of three conceptual rules (conjunctive, disjunctive, conditional). It was expected that the order of rule difficulty and subjects' truth table problem solving strategies would vary as a function of the type of conceptual task and IQ level.

Rejection of the hypothesis of homogeneity of variance precluded direct comparison of AI and RL tasks. Separate analyses of variance for each task type examined subjects' error rates, hypotheses, and trials to criterion.

Results revealed an effect of IQ level on trials to criterion for both tasks. Superior IQ subjects performed significantly better than did normal IQ subjects on this measure. The main effect of conceptual rule revealed a conjunctive (easiest), disjunctive, conditional (most difficult)

order of difficulty for the AI task. In the RL task, there was a reversal of difficulty between the conjunctive and disjunctive rules. In both tasks, the main effect was consistently due to the difficulty of the conditional rule for both IQ groups. Subjects' problem solving strategies were examined in the context of the logical truth table of stimulus classification for bidimensional concepts. No effect of IQ was found on problem solving strategy. A main effect of truth table class was obtained for the RL task only. This effect showed TT and FF classes to be easier than the TF and FT classes for all rules.

Rule difficulty and problem solving strategy were discussed in terms of the Sawyer-Johnson inference model. The applicability of the model to AI and RL tasks was considered.

INTRODUCTION

The primary definitions of intellect and intelligence in _Webster's New World Dictionary_ (1974) refer to the abilities to perceive relationships and differences, to learn or understand from experience, to acquire and retain knowledge, and to use reason in effectively solving problems or directing conduct. An examination of the experimental literature on problem solving and conceptual behavior reveals that these same general abilities apparently differentiate successful and unsuccessful experimental subjects. This study investigates and attempts to determine the extent to which the abilities defined as "intelligence" (as expressed by the IQ) relate to problem solving and conceptual abilities (as demonstrated by performance on concept learning tasks). This determination is made by examining subjects' performance on concept learning tasks as a function of task difficulty and intelligence.

In the study of conceptual behavior, a class concept is generally characterized by the presence or absence of one or more stimulus values and a rule specifying the necessary relationship between the relevant attributes (Haygood & Bourne, 1965). In a bidimensional concept, there are two relevant attributes. With such two-valued (bidimensional) concepts, eight unique relationships, or rules of combination, can be identified. Of these eight rule forms, four are "primary" relationships and four are their exact compliments (Salatas & Bourne, 1974). Where "A," "B" represent the two relevant attributes, the four primary rule forms are: conjunctive (A and B); disjunctive (A or B); conditional (if A then B); and biconditional (if A then B, and if B then A). The present study examines the relative difficulty of the first three of these primary rule forms (conjunctive, disjunctive, conditional), as a function of the type of concept learning task, and the subjects' level of intelligence.

Differences in the difficulty of conceptual rule forms may be examined in several ways, depending on the information available to the subject. In attribute identification (AI) problems, the subject is told the rule which defines the necessary relationship between the two important stimulus values. The subject's task is then to discover which two values are relevant to the concept. In a reception paradigm, stimuli are presented sequentially. For each stimulus, the subject gives a yes or no category response and is provided with immediate feedback concerning the correct classification of the stimulus. As the subject gains information regarding correct classification, he will eventually discover which two stimulus values are related in the manner defined by the given rule.

In a rule learning (RL) task, the subject is told which two stimulus values are important to the concept. In this case, the subject must then discover the rule which specifies the necessary relationship between the given relevant values. Stimulus presentation and informative feedback follow the same procedural methodology (reception paradigm) as that used in the attribute identification (AI) task. As the subject gains correct classification information, it will eventually become apparent which rule form defines the necessary relationship between the two given relevant stimulus values.

This study focuses on the difference in difficulty of the bidimensional rules in both AI (attribute identification) and RL (rule learning) tasks. One of the assumptions here is that the abilities necessary for successful performance on these tasks is a function of intelligence. In looking at the difficulty of the bidimensional rules, it is also assumed that, as difficulty increases, the subject's abilities will be put to greater test. As this occurs, performance differences between subjects of greater and lesser abilities will increase. Differences in bidimensional rule difficulty have been revealed in numerous empirical investigations of both AI and RL problems. However, the order of difficulty is not always the same between task types.

In RL tasks, the order of difficulty among the four primary rules has been reliably found to be, from least to most difficult: conjunctive, disjunctive, conditional, and biconditional (Bourne, 1970; Bourne & Guy, 1968a, 1968b; Neisser & Weene, 1962; Reznick & Richman, 1976; Salatas & Bourne, 1974)

In spite of the consistency found in the order of rule difficulty in rule learning tasks, a number of theoretical interpretations of rule difficulty have been proposed. Neisser and Weene (1962), for example, proposed a system of logical complexity for the psychological processes required by different rules. Their analysis placed conjunctive, disjunctive, and conditional rules in the same (easiest) category. Bruner, Goodnow and Austin (1956), on the other hand, have suggested that subjects develop a strategy whereby they focus on the attributes of a positive instance (i.e., a member of the stimulus class concept) and compare subsequent stimuli by varying one dimension at a time (conservative focusing). Bourne and Guy (1968b) examined subjects' utilization of information from negative and positive instances for conjunctive, disjunctive and conditional rules on both RL and AI problems. Their results indicated that subjects may use positive and negative instances differently, depending on the type of problem and the rule. For RL tasks, subjects performed best when information from both positive and negative instances was available. On AI problems, performance was best when information from the smaller, more homogeneous class of instances (positive or negative) was available. As the variables of class size and homogeneity are determined by rule, the difficulty of the rule will increase as class size is increased and/or as homogeneity decreases.

Bourne (1970) and Salatas and Bourne (1974) also examined the theoretical models which attempt to account for the differences in difficulty found for the bidimensional rules. These various models all predict a different order of difficulty for the four primary bidimensional rules. The association model, which employs a stimulus-response logic, predicts equal difficulty of all rules. The hierarchy of logical operations model of rule complexity (Neisser & Weene, 1962) predicts conjunctive, disjunctive and conditional rules to be equally difficult, while the biconditional rule is more difficult. Hovland's (1952) model predicts conjunctive easiest, with disjunctive and biconditional equal, followed by conditional, and then disjunctive equal to biconditional as most difficult. The variability in the predictions derived from these models fails to account for the data which consistently reveals a conjunctive, disjunctive, conditional, biconditional order of rule difficulty from least to most difficult.

Research by Bourne (1970), Salatas and Bourne (1974), and that of Sawyer & Johnson (cited in Salatas & Bourne, 1974) in rule learning have led to the development of a model which suggests that subjects acquire a truth table problem solving strategy based on the classification of stimulus values. In bidimensional concepts, where the class concept is defined by two stimulus values and a combinational rule, the logical truth table consists of four classes of events: True, True (TT); False, False (FF); True, False (TF); and False, True (FT). These classes represent a factorial combination of the presence (T) or absence (F) of the two relevant values (Salatas & Bourne, 1974).

In the model, it is assumed that naive subjects approach the RL problem solving task with a bias favoring a conjunctive rule. Bruner, et al. (1956) have referred to this bias as a "conjunctive set." In developing a truth table strategy, the subject must learn to classify stimuli differently for each rule. Given a conjunctive bias, the extent to which the stimulus assignments differ from those for a conjunctive rule determines the difficulty of the rule.

The results of Salatas and Bourne's (1974) investigation suggest that for RL problems, subjects make fewer classification errors when (a) TT instances were positive, (b) FF instances were negative, and when (c) TF and FT instances were in the same category as FF instances. This particular classification scheme suggests the operational characteristics of a conjunctive set, in that it is facilitative only for a bidimensional conjunctive rule. This supports the contention that when stimuli are classified in categories according to a different rule, some degree of difficulty is introduced. Salatas and Bourne (1974) calculated the degree of rule difficulty on the basis of the distribution of stimuli across truth table classes. The order of difficulty predicted by the model was supported by the results for the four primary bidimensional rules (Salatas & Bourne, 1974).

The order of rule difficulty obtained with AI tasks is not as consistent as that found with RL problems. Taplin (1971, 1975) has reported instances in which the difficulty of disjunctive and conjunctive rules was reversed, and where the biconditional rule was equivalent in difficulty to the disjunctive rule. He pointed out, however, that differences in the obtained order of rule difficulty are not surprising given the different tasks employed. In examining subjects' hypothesis testing on AI problems, Taplin (1975) suggested that differences in rule difficulty may be a function of the processing required in confirming or disconfirming hypotheses using positive or negative instances. The additional processing for negative instances derives from transforming knowledge about what the stimulus is not, to what it is. For AI problems, by virtue of the given rule, subjects should not display as strong a conjunctive bias as in RL tasks. It seems reasonable to assume, however, that there could be some carry-over in terms of processing demands involved in applying a newly learned rule to AI tasks. Should this be the case, such bias should be reflected in the order of rule difficulty obtained for both RL and AI problems.

It is noteworthy that most studies involving successive rule learning have found positive inter and intra-rule transfer effects (Bourne & Guy, 1968a, 1968b) and that a reduction of differences in rule difficulty occurs rapidly across trials (Bourne, 1970; Haygood & Bourne, 1965; Salatas & Bourne, 1974). This suggests that subjects acquire an effective problem solving strategy rather quickly and that differences in rule difficulty are most likely to be obtained with naive subjects. Further, it suggests that subjects may acquire the truth table problem solving strategy at different rates. The model proposed by Sawyer and Johnson and expanded by Salatas and Bourne (1974) assumes that pre-experimental bias is influential in determining the rate at which subjects acquire a truth table strategy for different rules. Thus, subjects enter the experimental situation with different amounts of experience with conceptual problems, and possibly with non-conjunctive biases toward the conceptual problem. This latter possibility has been examined by Dominowski and Wetherick (1976) and Reznick and Richman (1976). Results from both of these studies, which used direct assessment of pre-experimental bias, indicate that not all subjects exhibit an initial conjunctive set. In examining subjects' initial truth table classification strategies, Reznick and Richman (1976) report that 29 percent of the subjects receiving one set of relevant stimulus values, and 12 percent of the subjects receiving another set, revealed a conjunctive bias. Similarly, Dominowski and Wetherick (1976) report that nearly 16 percent of their subjects exhibited an initial conjunctive bias. Results of these investigations indicate that the stimulus properties of class complexity (i.e., the number of unique stimuli within each truth table class) and frequency (i.e., the total number of stimuli in each truth table class) may effect initial bias (Reznick & Richman, 1976) and transfer of learning of correct stimulus classification within each truth table class (within-class transfer)

(Dominowski & Wetherick, 1976). In both of these investigations, the results indicate that initial classification bias affects subsequent rule learning in the manner proposed by the Sawyer and Johnson model. However, these results suggest an expansion of the model which would account for non-conjunctive bias in conceptual rule learning.

This study is also concerned with the proposition that initial rule difficulty and the acquisition of conceptual problem solving strategies may differ for subjects of normal and superior intelligence. In light of the commonly referred to relationship between conceptual abilities and level of intelligence, this proposition appears to have face validity. Further, numerous intelligence tests are designed in whole or in part to measure subjects' conceptual abilities. Butcher (1968) points to the surprisingly poor level of integration between the study of individual differences and the study of concept learning. One purpose of the present research is to examine, in an exploratory fashion, such an integration.

The experimental literature does provide some support for the proposition that intelligence and conceptual abilities are related. In a series of studies, Osler and her associates (Osler & Fivel, 1961; Osler & Trautman, 1961; Osler & Weiss, 1962) have investigated the role of individual differences and conceptual behavior. Osler and Fivel (1961) found that subjects with superior IQ exhibit sudden, all or none learning consistent with an hypothesis testing strategy. On the other hand, normal IQ subjects show gradual learning consistent with a continuity theory interpretation. Other research by Osler has revealed that normal and superior IQ level subjects are differently affected by the number of stimulus dimensions (Osler & Trautman, 1961) and experimental instructions (Osler & Weiss, 1962). On the basis of their results, Osler and Trautman (1961) conclude that "the process mediating concept attainment is a function of intelligence" (p.9). An extension of this conclusion would suggest that the difficulty of bidimensional conceptual rules and the acquisition of an effective problem solving strategy might also be a function of intelligence.

A major assumption in this examination of rule difficulty is that subjects will exhibit more rapid concept attainment where their pre-experimental bias favors the relevant rule form (Dominowski & Wetherick, 1976; Reznick & Richman, 1976). Thus, without assuming a conjunctive set, and in the absence of direct assessment of pre-experimental bias, it is assumed that conceptual bias will be revealed in the obtained order of rule difficulty as based on the number of trials to criterion for each rule. Therefore, should differences in conceptual bias between normal and superior IQ subjects obtain, as suggested by Osler and Trautman (1961), these should be revealed in the order of rule difficulty. In this context, it is expected that for both AI and RL tasks, performance differences between IQ groups will increase as a direct function of the obtained order of rule difficulty for each group. Thus, performance differences between IQ groups are expected to be greatest on the rules found to be most difficult and smallest on the rules found to be easiest. This result is expected regardless of whether the obtained order of rule difficulty is the same for the two IQ groups. Similarly, should both IQ groups reveal the same order of rule difficulty, it is expected that for a given rule, performance differences between the two IQ groups will increase as a function of the obtained order of difficulty.

In this study, there are 54 possible two-valued concepts (108 possible ordered pairs for the conditional rule). In the AI task, the subject does not know which two values are relevant. In the RL task condition, there are four possible rules, the correct one of which is unknown to the subject. Therefore, it is assumed that the processing demands in the AI task condition are greater than those in the RL task condition. Given this differential in processing demands, it is expected that obtained differences between normal and superior IQ subjects will be greater in the AI condition than in the RL condition (Osler & Fivel, 1961; Osler & Trautman, 1961). Although it is not assumed that the AI and RL task conditions will yield the same results, it is of interest to the present study that the task conditions be roughly equivalent. As such, procedures and subject instructions are identical until subjects are required to solve either AI or RL problems, and stimulus materials are the same in both conditions. In this way, it is possible to attribute obtained differences between AI and RL conditions solely to the nature of the task or the type of processing required by the task (Bruner, Goodnow & Austin, 1956).

In assessing the acquisition of a truth table strategy, subjects' performance is examined for each truth table class. As the subject learns to correctly assign stimuli to a truth table class, errors in that class decrease and eventually no errors are made for that class of stimuli (Bourne, 1970). It is expected that superior IQ subjects learn to assign stimuli to correct truth table classes more rapidly than normal IQ subjects. Thus, the error rate for any given truth table class should be greater for subjects in the normal IQ group than for those in the superior IQ group. Additionally, it is expected that the proportion of classification errors will decrease more slowly across trials for the normal IQ group than for the superior group, as a function of the extent to which classification of stimuli for the relevant rule differs from that for the preferred (i.e., pre-experimentally biased) rule.

The model of truth table classification strategy developed by Sawyer and Johnson and expanded by Salatas and Bourne (1974) applies to RL tasks. This is the case because when the subject is given the relevant stimulus values, it is immediately apparent when the values are (T) or are not (F) present. In this way, it is easy for the subject to classify stimuli on the basis of the presence of the relevant values, particularly following a minimal amount of practice (Bourne, 1970, 1974). It is of interest to the present study that the ease with which subjects acquire this type of classification strategy for RL problems may be a function of intelligence. It is also of interest that this type of classification strategy may be useful in AI problems as well. Since subjects are thoroughly instructed as to the nature of both AI and RL problems, it is expected that the importance of the presence or absence of the relevant stimulus values will be apparent to subjects in both task conditions (Bourne & Guy, 1968a).

For subjects in the AI condition, although the two relevant values are not known, the correct classification of stimuli will still be linked to such a truth table strategy. Due to the increased complexity of applying a truth table strategy to AI problems, relative to RL problems, it is expected that the difference in acquisition rates between normal and superior IQ groups will increase as a function of the task type, where as for RL problems, the difference is lesser than for AI problems. This is consistent with the general proposition that AI tasks are more difficult than RL tasks (Bourne & Guy, 1968b; Haygood & Bourne, 1965).

METHOD

Subjects

Subjects were 48 paid ($3.00/hr.) participants. Subjects were recruited from a number of sources, primarily from summer session courses at Loyola University of Chicago. Subjects were 29 females and 19 males, between 18 and 34 years of age. A total of 50 subjects participated in the experiment, however, two normal IQ subjects were randomly eliminated so as to yield equal numbers of normal and superior subjects under each treatment condition. The average length of an experimental session was one to one and one-half hours.

Design

A 3 x 2 x 2 factorial design with variables (a) conceptual rule (conjunction, inclusive disjunction, conditional); (b) task type (attribute identification [AI], rule learning [RL]); and (c) intellectual level (normal, superior) was employed. Subjects were nested within IQ and task type and were crossed with rule type.

Materials

Assessment of intelligence. Prior to the concept learning phase of the experiment, all subjects were given four of the eleven subtests comprising the Wechsler Adult Intelligence Scale (WAIS). The subtests used consisted of two Verbal subtests, Similarities (S) and Vocabulary (V); and two Performance subtests, Picture Completion (PC) and Picture Arrangement (PA).

In selecting these four subtests, several criteria were considered. Due to the constraints of the proposed design, it was necessary to evaluate intellectual level and execute experimental manipulations in the same session. This precluded use of the WAIS Full Scale IQ in differentiating subjects. For this reason, it was necessary to differentiate IQ on the basis of either a shorter test or a subset of the tests given in the full scale WAIS. Due to the widespread use and standardization of the WAIS, the latter choice seemed advisable. The relevance to conceptual behavior of the subtests used in the present study was based on published descriptions of the subtests by Zimmerman and Woo-Sam (1973) and Matarazzo (1972), as well as loading on Cohen's (1957) general intelligence factor (G).

In their consideration of the S subtest, Zimmerman and Woo-Sam (1973) describe performance on similarities as representing "a specific application of man's ability to generalize, abstract, and find relationships that are not obvious at first . . . emphasizing <u>concept formation</u> rather than word difficulty . . . [and] making implicit or explicit use of classificatory relationships." (P. 87, emphasis added).

Matarazzo (1972) describes as important in the S subtest "the individual's ability to perceive the common elements of the terms he is asked to compare and, at higher levels, his ability to bring them under a single concept" (p. 205), as well as the ability to "discriminate between essential and superficial likenesses" (p. 207). Cohen's (1957) factor analysis reveals Similarities as a good measure of G ($r = 0.77$). Zimmerman and Woo-Sam (1973) consider this correlation to reflect a capacity for verbal concept association.

Although the V subtest does not involve abilities clearly associated with concept formation, it is considered to be one of the best measures of G. Cohen's (1957) data reveal a very strong (0.83) correlation. Zimmerman and Woo-Sam (1973) have stated that performance on the V subtest "indicates sensitivity to new information and ideas and the ability to store and associatively regroup these as the occasion demands." They note that "by inference, it reveals classificatory and conceptualizing skills."

(P. 108). These considerations, in addition to the fact that Vocabulary has the highest reliability of the WAIS subtests, support the inclusion of V in the short form for assessment of intellectual functioning.

Cohen's (1957) analysis reveals that PC obtained the highest loading of the WAIS performance subtests on the general intelligence factor (r = .75). Other major factors associated with PC include Verbal Comprehension, Perceptual Organization, and Freedom from Distractability (Zimmerman and Woo-Sam, 1973). Zimmerman and Woo-Sam also point out as important the ability to identify the interrelationships among the various major elements of the stimulus items. This ability is clearly involved in solving concept identification problems and is consistent with Matarazzo's (1972) statement that Picture Completion "measures the individual's basic perceptual and conceptual abilities . . . ". (P. 210). Matarazzo also notes the importance of the individual's ability to differentiate essential from non-essential details. Although PC does not directly measure conceptual ability, success on this subtest involves skills similar to those required in conceptual tasks.

The PA subtest involves the same skills as those associated with PC in the identification of essential features and relating parts to the whole. Zimmerman and

Woo-Sam (1973) have also noted sequential planning, synthesis of parts, and the ability to see cause-effect relationships as important factors in the PA subtest. Cohen's analysis reveals a moderate ($r = .70$) correlation with G.

In addition to the above mentioned criteria, the reliability coefficients and standard errors of measurement (WAIS Manual, 1955) for each subtest were considered in establishing the short form used in the present study. These figures for the Age 25-34 standardization sample are represented on the diagonal in Table 1.

Table 1 also depicts the intercorrelation matrix (WAIS Manual, 1955) for these four subtests and the WAIS Full Scale IQ. This correlation matrix was submitted to a stepwise multiple regression analysis (Nie, Hull, Jenkins, Steinbrenner & Bent, 1975) which provided weights for predicting the WAIS Full Scale IQ: Similarities (.20); Vocabulary (.37); Picture Completion (.24) and Picture Arrangement (.25), (multiple, $R = .90$). In order to predict IQ from the four subtests, each subject's raw scores were converted to scaled scores, multiplied by the obtained beta weights, and summed by Equation 1.0:

Table 1[a]

Intercorrelation of WAIS Subtests and WAIS Full Scale IQ[b]

		Subtests				
		S	V	PC	PA	FS
Similarities	(S)	r=.85 SE=1.15	.74	.56	.52	.74
Vocabulary	(V)		r=.95 SE=.67	.61	.62	.82
Picture Completion	(PC)			r=.85 SE=1.73	.57	.72
Picture Arrangement	(PA)				r=.60 SE=1.73	.72
Full Scale IQ	(FS)					r=.97 SE=2.60

Note. Reliability coefficients (r) and standard errors of measurement (SE) appear on the diagonal.

[a]Adapted from the WAIS Manual, 1955, p. 13, p. 16.

[b]These figures apply to the age 25-34 standardization sample.

$$\text{Estimated IQ} = 100 + 15\left[\sum_{i=1}^{4} (Zx_i b_i)\right] \quad (1)$$

Where: $Zx_i = \left(\frac{x_i - 10}{3}\right)$

x_i = scaled score for subtest i

b_i = regression weight from multiple R.

Normal IQ level was defined as predicted scores in the range of 90 to 114. The lower boundary for the normal range follows that used by Osler and Fivel (1961). The upper boundary was raised above that used by Osler and Fivel since a higher mean IQ was expected in the present sample of college students. Superior IQ subjects were classified as those with predicted IQ in excess of 115.

All materials for the assessment of intelligence were taken from the Wechsler Adult Intelligence Scale and the WAIS Manual. Each of the four subtests described above was given in their entirety as they would be in the administration of the full scale WAIS. The WAIS subtests were administered by the Experimenter who has had graduate level training and experience in administration and scoring of the Wechsler Intelligence Scales.

Concept learning materials. Stimuli consisted of geometric designs presented on 5" x 8" white index cards. These stimuli varied along four three-valued dimensions: Number of Figures (one, two or three);

Color of Figures (red, blue or green); Shape of Figures (circle, square or triangle) and Shading of Figures (open, diagonal or cross hatched). For each problem, a subset of 36 of the 81 possible patterns was presented sequentially in a predetermined order subject to the following constraints:

1. For each problem, stimuli equally represented each of the four truth table classes (TT, TF, FT, and FF), i.e., nine each;

2. Stimuli were presented in blocks of nine, such that the naturally occuring ratio of negative and positive instances for the relevant rule was preserved; and

3. The 36 stimuli were repeated twice, as necessary, for the subject to reach the criterion of 12 consecutive correct stimulus classifications, three for each truth table class, for problem solution.

Procedure

There were two phases in this study. The first phase consisted of administration of the four WAIS sub-tests (S, V, PA, PC) and differentiation of subjects by level of intelligence. In phase two, subjects were trained in the four primary bidimensional rules. Following training, subjects solved one problem for each of three rules: conjunctive, disjunctive, and conditional, in either an AI or RL paradigm.

As a control for systematic inter-rule transfer effects in both AI and RL conditions, the problem order for the three conceptual rules was counter-balanced, using six permutations of three rules in random rotation. Each subject received one problem utilizing each of the three conceptual rules. For subjects in the RL condition, an awareness of this procedure may have facilitated anticipation of the rule to be learned. That is, a 33 percent probability of any one rule on the first problem, a 50 percent probability of one of the two remaining rules on the second problem, etc. In order to offset this anticipation, two procedures were adapted. First, all subjects were instructed in one irrelevant rule (biconditional). Second, subjects were instructed that the relevant rule was to be determined by random selection with replacement among the four possible rules. Thus, the relevant rule could have been any one of four possible rules on any problem. In order to increase the believability of the random selection instruction, subjects were given four problems. The second in the series of four problems utilized the same rule as the first problem in the series. Only the first of these two problems was considered in the analysis.

Phase one. Subjects were informed that there were two phases in the experiment. Each subject was then given instructions pertaining to Phase 1 (see Appendix A).

Subjects were told that they would be given four tests taken from the Wechsler Adult Intelligence Scale. It was explained that these tests would be used as a measure of general intelligence only for purposes of comparing experimental participants, that results would be kept confidential, and that professional ethics would not allow the Experimenter to inform subjects of the outcomes of these measures. Subjects were given the four WAIS subtests in the respective order of their administration in the Full Scale WAIS (S, V, PC, PA).

Following the administration of the four WAIS subtests, subjects were given a short break before the start of Phase Two. The Experimenter then computed estimated IQ (see Equation 1.0) and assigned subjects to AI and RL task conditions on an alternating basis as a function of IQ level, so as to yield equal numbers of normal and superior IQ level subjects under each treatment.

<u>Phase two</u>. All subjects were instructed in the principles of the concept learning tasks (see Appendix A). The nature of the stimuli and the four primary bidimensional rules were explained and subjects were shown examples of the stimuli which represented each value of the four dimensions. For their reference during the task,

subjects were provided with a list of the four three-valued dimensions (see Appendix B) and a sheet explaining the four primary rules (see Appendix C). For each stimulus, subjects were required to make a category response by saying either "yes" or "no," indicating membership or nonmembership in the concept class. Subjects received feedback from the Experimenter who indicated the correct category response by saying either "yes, it is" or "no, it is not."

Subjects were given practice utilizing a card sorting procedure. The card sorting procedure was repeated for each rule with 12 of the 52 playing cards representing three instances from each truth table class. For each rule, the sorting procedure was repeated as necessary for subjects to correctly sort all twelve cards according to the relevant rule and values, which were given. Errors were corrected and explained immediately for each stimulus. When repetition was necessary, the relevant values were changed and the rule remained the same until the practice criterion was reached.

Following the practice procedure, subjects were instructed for either AI or RL problems (see Appendix A). Subjects were given as much time as necessary to respond to each stimulus card and immediate feedback was provided.

After being given the correct response, the subject was given five seconds to view the stimulus before the next card was presented.

Upon completion of the four concept learning problems, subjects were requested to indicate the extent to which they believed the random rule selection instruction on a Likert-type five point scale. This procedure was designed to indicate the extent to which subjects in the Rule Learning (RL) condition may have anticipated the rule to be learned.

At the conclusion of the experimental session, subjects were thanked and paid for their participation. A brief explanation of the experiment was offered and subjects' questions were answered.

RESULTS

Pooled within group estimates of error variance were computed separately for AI and RL task conditions. Homogeneity of variance between task conditions was then tested with the F statistic at the .25 level of significance. This alpha level was set in order to avoid the type two error of failing to reject a false null hypothesis of homogeneity (i.e., no difference). Six of the 10 tests for homogeneity of variance revealed significant differences between the two task conditions for each of the following dependent variables. On reaching criterion, F (22,22) = 2.938, $p < .01$ and F (44,44) = 3.958, $p < .01$, for subjects within IQ and subjects x rule within IQ, respectively. On proportion of total errors, F (22,22) = 2.048, $p < .10$ and F (44,44) = 1.373, $p < .10$, for subjects within IQ and subjects x rule within IQ, respectively. On proportion of errors within truth table class, F (22,22) = 2.172, $p < .05$ and F (66,66) = 1.869, $p < .01$, for subjects within IQ and subjects x truth table class within IQ, respectively.

The F test for homogeneity of variance failed to reach significance on the variable correct hypothesis for both subjects within IQ and subjects x rule within IQ. Similarly, there was a failure to reject the hypothesis of homogeneity of variance on the proportion of errors within truth table class for subjects x rule within IQ and subjects x rule x truth table class within IQ. Thus there was no significant difference in variance between the two task conditions on these dependent variables. On the whole, however, the null hypothesis of homogeneity of variance between the AI and RL task conditions was rejected and all subsequent analyses were performed separately for each of the two task conditions.

Mean IQ scores and the corresponding variance was computed for both normal and superior IQ groups in the AI and RL task conditions. These figures can be found in Table 2. The strength of association between the dependent and independent variables was also computed. T - tests and computation of ω^2 (from Hays, 1973, p. 414) for each task condition showed that a significant proportion of the variance was accounted for by IQ level. For the AI task, $\omega^2 = .6648$, while for the RL task, $\omega^2 = .7125$, showing nearly equal amounts of variance accounted for by IQ in the two task conditions.

In order to evaluate the extent to which subjects

Table 2

Mean and Variance of IQ

for Normal and Superior Subjects

IQ Level	Mean	Variance
Superior		
AI Task	122.1	24.41
RL Task	120.3	17.39
Normal		
AI Task	108.3	25.72
RL Task	107.5	15.08

believed the random rule selection instruction, subjects' confidence ratings were examined. The mean confidence level on a five point Likert-type scale was 4.79, indicating a very high level of confidence in the veridicality of this instruction.

Due to the constraints placed on the stimulus set, for the conditional rule, it was possible for the subjects in the AI task condition to formulate an hypothesis which could not be disconfirmed. For subjects under this treatment condition, when an incorrect hypothesis was stated, the stimulus set was examined for possible disconfirmation. When the stated hypothesis could not be disconfirmed, the subject was given credit for the correct hypothesis . Of 17 subjects giving an incorrect hypothesis under the AI conditional rule treatment condition, five subjects stated hypotheses which could not be disconfirmed. For purposes of this analysis, those five subjects were treated as having stated the correct hypothesis.

<u>Attribute Identification</u>

A 2 (IQ level) x 3 (conceptual rule) analysis of variance was computed for the AI (Attribute Identification) task. The dependent variables for this analysis were: (a) the proportion of total errors to total responses; (b) statement of the correct hypothesis; and (c) reaching the criterion of 12 consecutive correct responses within the maximum of 72 trials. Table 3 presents a summary of this ANOVA. Part (i) contains the summary for the dependent variable of reaching criterion. Parts (ii) and (iii) present the summary for correct hypothesis and proportion of errors, respectively. For this task condition, the analysis revealed a main effect of conceptual rule on all three dependent measures. F (2,44) = 12.8701, $p < .01$, F (2,44) = 14.3257, $p < .01$, F (2,44) = 13.5539, $p < .01$, for criterion, hypothesis, and errors, respectively. Table 4 shows the mean percentage of subjects failing to reach criterion as a function of conceptual rule. Table 5 shows the mean percentage of subjects failing to state the correct hypothesis as a function of conceptual rule and IQ level, and Table 6 shows the mean proportion of errors to total responses as a function of conceptual rule and IQ level.

The ANOVA also revealed a significant interaction of rule and IQ level on subjects' statements of the correct hypothesis in the AI task. F (2,44) = 3.5814, $p < .05$. The figures in the matrix of Table 5 represent the percentage of subjects failing to state the correct hypothesis as a function of the IQ level, conceptual rule interaction. For both normal and superior IQ levels, the order of rule difficulty was the same (in order of descending difficulty):

Table 3

Attribute Identification Task

2(IQ Level) x 3(Conceptual Rule) ANOVA Summary

Source	SS	df	MS	F
		Part (i): Criterion		
Between				
IQ	.001389	1	.001389	.1209
Subjects (IQ)	2.53	22	.11489	
Within				
Rule	2.25	2	1.625	12.8701**
IQ x Rule	.5278	2	.26389	2.09
Subjects x Rule (IQ)	5.56	44	.12626	
		Part (ii): Hypothesis		
Between				
IQ	.00556	1	.00556	.3284
Subjects (IQ)	3.722	22	.16919	
Within				
Rule	3.11	2	1.56	14.3257**
IQ x Rule	.7778	2	.3889	3.5814*
Subjects x Rule (IQ)	4.778	44	.10858	

Table 3, cont.

Source	SS	df	MS	F
		Part (iii): Errors		
Between				
IQ	.8888	1	.8888	.0064
Subjects (IQ)	3079.04	22	139.96	
Within				
Rule	1912.11	2	956.06	13.5539**
IQ x Rule	448.11	2	224.06	3.1764
Subjects x Rule (IQ)	3103.64	44	70.54	

** $p < .01$

* $p < .05$

Table 4

Mean Percentage of Subjects Failing to Reach Criterion in the AI Task*

Conceptual Rule	Conjunctive	Disjunctive	Conditional
	00	12.5	50

*These figures are based on n = 24 subjects

Table 5

Mean Percentage of Subjects Failing to State the Correct Hypothesis in the AI Task

	Conceptual Rule		
IQ Level	Conjunctive	Disjunctive	Conditional
Normal	0	33	42
Superior	0	0	58
	0	17	50

Note. The marginal column totals represent the means for the main effect of rule. The figures within the matrix represent the Rule x IQ interaction.

Table 6

Mean Proportion of Errors to Total Responses for the AI Task Condition

	Conceptual Rule			
IQ Level	Conjunctive	Disjunctive	Conditional	
Normal	22.33	23.08	28.33	/ 24.58
Superior	18.67	19.25	35.17	/ 24.36
	20.50	21.16	31.75	

Note. These figures represent the mean proportion of errors x 100.

conditional, disjunctive, and conjunctive.

In order to examine the differences between the rules which contributed to the significant overall main effect of rule on the dependent measure of reaching criterion (see Table 4), a Newman-Keuls test was performed. Utilizing the q_r statistic (see Winer, 1971), this test revealed significant differences between the conditional rule and each of the other rules (i.e., conjunctive and disjunctive). $S_{\bar{B}}\ q_{.95}$ (3,44) = .2487, $p < .05$; and $S_{\bar{B}}\ q_{.95}$ (2,44) = .2066, $p < .05$, for the difference between conjunctive and conditional; and disjunctive and conditional, respectively.

An analysis of simple main effects on the interaction of IQ level and rule on the dependent measure of stating the correct hypothesis (see Table 4) was performed. This analysis revealed a significant effect of rule on both IQ groups. F (2,44) = 5.374, $p < .01$, for normal IQ subjects, and F (2,44) = 12.534, $p < .01$, for superior IQ subjects. This simple main effects analysis also showed a significant effect of IQ on the disjunctive rule, F (1,63) = 5.125, $p < .05$. The simple main effect of IQ on the conjunctive and conditional rules was not significant.

A Newman-Keuls test on the differences between rules for the mean proportion of total errors revealed relationships similar to those found on the criterion measure (see Table 6). For the difference between conditional and conjunctive rules, $S_{\bar{B}}\ q_{.95}\ (3,44) = 5.880$, $p < .05$; and for the difference between conditional and disjunctive rules, $S_{\bar{B}}\ q_{.95}\ (2,44) = 4.886$, $p < .05$.

A contrast on the mean proportion of total errors also revealed a significant difference between the conjunctive-disjunctive rule pair and the conditional rule, $F\ (1,69) = 27.02$, $p < .001$. The difference between the conjunctive and disjunctive rules was not significant.

In order to examine the proportion of errors to total responses within each truth table class, a 2(IQ level) x 3(conceptual rule) x 4(truth table class) analysis of variance was performed for the AI task condition. Table 7 represents this ANOVA in summary form. This analysis showed a main effect of conceptual rule, $F\ (2,44) = 12.9437$, $p < .01$, with rules ordered conjunctive, disjunctive and conditional, respectively, from least to most difficult. This analysis also revealed significant interactions in the AI task condition for conceptual rule and IQ level, $F\ (2,44) = 3.2788$, $p < .05$, and between conceptual rule and truth table class, $F\ (6,132) = 7.1484$, $p < .01$. Table 8 represents the proportion of errors to total responses, summed across truth table class, as a function of rule and IQ level. Table 9 shows the proportion of errors to

Table 7

Attribute Identification Task

2(IQ Level) x 3(Conceptual Rule) x 4(Truth Table Class) ANOVA

Summary for Truth Table Class Errors

Source	SS	df	MS	F
Between				
IQ	10.125	1	10.125	0.0182
Subjects (IQ)	12240.44	22	556.38	
Within				
Rule	7299.52	2	3649.76	12.9437**
IQ x Rule	1849.08	2	924.54	3.2788*
Subjects x Rule (IQ)	12406.75	44	281.97	
Class	2106.24	3	702.08	1.8110
IQ x Class	597.90	3	199.30	0.5141
Subjects x Class (IQ)	25587.04	66	387.68	
Rule x Class	12691.80	6	2115.30	7.1484**
IQ x Rule x Class	258.10	6	43.02	0.1454
Subjects x Rule x Class (IQ)	39060.23	132	295.91	

** $p < .01$

* $0 < .05$

Table 8

Mean Proportion of Errors to Total Responses for Subjects in the AI Task Condition

	Conceptual Rule				
IQ Level	Conjunctive	Disjunctive	Conditional		
Normal	22.90	23.21	28.35	/	24.82
Superior	18.98	19.21	35.15	/	24.45
	20.94	21.21	31.75		

Note. These figures represent the the mean (proportions) x 100. The marginal column totals represent the means for the main effect of rule, while the means within the factorial matrix represent rule by IQ interaction. These figures are summed across truth table class.

Table 9

Mean Proportion of Errors to Total Responses

As a Function of Truth Table Class and Rule in the AI Task

	Truth Table Class			
Rule	TT	TF	FT	FF
Conjunctive	22.92	21.92	30.25	8.67
Disjunctive	7.79	20.96	27.21	28.88
Conditional	32.29	38.58	24.50	31.62

Note. Figures represent means (proportions) x 100.

total responses within each truth table class as a function of conceptual rule summed across IQ levels.

An additional 2(IQ level) x 3(conceptual rule) analysis of variance was performed for the AI task condition using the number of trials to criterion as the dependent measure. For purposes of this analysis, subjects failing to reach criterion within 72 trials were assigned the maximum score of 72 trials. Results of this analysis indicate a significant main effect of IQ, $\underline{F}$ (1,22) = 5.07, $\underline{p} < .05$, and rule, $\underline{F}$ (2,44) = 15.75, $\underline{p} < .05$, on number of trials to criterion. Table 10 presents a summary of this ANOVA, while Table 11 shows the mean number of trials to criterion as a function of IQ and conceptual rule.

A Newman-Keuls test revealed a significant difference between superior and normal IQ groups, $S_{\bar{A}}\, q_{.95}$ (2,22) = 9.487, $\underline{p} < .05$; and between all rule pairs, $S_{\bar{B}}\, q_{.95}$ (2,44) = 9.798, $\underline{p} < .05$ for the difference between the conjunctive-disjunctive and disjunctive-conditional rule pairs, and $S_{\bar{B}}\, q_{.95}$ (3,44) = 11.792, $\underline{p} < .05$ for the difference between the conjunctive and conditional rules.

<u>Rule Learning</u>

A 2(IQ level) x 3(conceptual rule) analysis of variance was computed for the RL task condition. As in the AI task, the dependent variables for this analysis

Table 10

Attribute Identification Task

2(IQ Level) x 3(Conceptual Rule) ANOVA

Summary for Number of Trials to Criterion

Source	SS	df	MS	F
Between	10151.5	23	441.37	
IQ	1901.39	1	1901.39	5.07*
Subjects (IQ)	8250.11	22	375.00	
Within	22090.0	48	460.21	
Rule	8937.58	2	4468.79	15.75**
IQ x Rule	668.36	2	334.18	1.18
Subjects x Rule (IQ)	12484.06	44	283.73	
Total		71		

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

Table 11

Mean Number of Trials to Criterion

As a Function of IQ Level and Rule in the AI Task

	Conceptual Rule				
IQ Level	Conjunctive	Disjunctive	Conditional		
Normal	33.25	47.08	53.33	/	45.56
Superior	22.67	29.50	53.67	/	35.28
	27.96	38.29	55.00		

Note. Subjects failing to reach criterion were assigned a maximum of 72 trials. The marginal column totals represent the means for the main effect of rule, while the marginal row totals represent the means for the main effect of IQ level.

were: (a) subjects reaching criterion of 12 consecutive correct responses within a maximum of 72 trials; (b) subjects' statement of the correct hypothesis; and (c) proportion of errors to total responses. A summary of the ANOVA for each of these dependent measures is represented in Parts (i), (ii) and (iii) of Table 12.

For the RL task condition, the 2 x 3 ANOVA revealed a significant main effect of conceptual rule on statement of correct hypothesis, $\underline{F}$ (2,44) = 8.8847, $\underline{p} < .01$, and proportion of total errors, $\underline{F}$ (2,44) = 15.2778, $\underline{p} < .01$. Table 13 shows the percentage of subjects failing to state the correct hypothesis as a function of conceptual rule and IQ level. Table 14 shows the mean proportion of errors to total responses as a function of conceptual rule and IQ level.

A Newman-Keuls test on the statement of correct hypothesis showed significant differences on all possible ordered comparisons of rule pairs (see Table 13). For conjunctive-disjunctive and conjunctive-conditional pairs, $S_{\bar{B}}\, q_{.95}$ (2,44) = .05757. For the disjunctive-conditional comparison, $S_{\bar{B}}\, q_{.95}$ (3,44) = .069286. Similarly, a Newman-Keuls test revealed significant differences in total errors (see Table 14) between the disjunctive and conditional rules, $S_{\bar{B}}\, q_{.95}$ (2,44) = 4.161.

In order to examine the proportion of errors within

Table 12

Rule Learning Task

2(IQ Level) x 3(Conceptual Rule) ANOVA Summary

Source	SS	df	MS	F
Part (i): Criterion				
Between				
IQ	.001389	1	.001389	0.3548
Subjects (IQ)	.8611	22	.003914	
Within				
Rule	.2500	2	.12500	3.1936
IQ x Rule	.00278	2	.001389	0.3548
Subjects x Rule (IQ)	1.722	44	.003914	
Part (ii): Hypothesis				
Between				
IQ	.500	1	.500	3.8824
Subjects (IQ)	2.833	22	.12878	
Within				
Rule	1.75	2	.8750	8.8847**
IQ x Rule	.5833	2	.29167	2.9616
Subjects x Rule (IQ)	4.333	44	.009848	

Table 12, cont.

Source	SS	df	MS	F
Part (iii): Errors				
Between				
IQ	122.72	1	122.72	1.7955
Subjects (IQ)	1503.71	22	68.35	
Within				
Rule	1569.361	2	784.68	15.2778**
IQ x Rule	232.03	2	116.01	2.2588
Subjects x Rule (IQ)	2259.88	44	51.36	

** $p < .01$

Table 13

Mean Percentage of Subjects Failing to State the Correct Hypothesis in the RL Task

	Conceptual Rule		
IQ Level	Conjunctive	Disjunctive	Conditional
Normal	17	0	58
Superior	8	0	17
	12.5	0	37.5

Note. The marginal column totals represent the means for the main effect of rule

Table 14

Mean Proportion of Errors to Total Responses for Subjects in the RL Task Condition

	Conceptual Rule		
IQ Level	Conjunctive	Disjunctive	Conditional
Normal	10.08	11.50	21.50
Superior	12.42	5.42	17.42
	11.25	8.46	19.46

Note. These figures represent the proportion of errors x 100.

each truth table class in the RL task condition, a 2(IQ level) x 3(conceptual rule) x 4(truth table class) analysis of variance was computed. A summary of this ANOVA is presented in Table 15. This analysis revealed significant main effects of conceptual rule, $\underline{F}$ (2,44) = 14.1362, $\underline{p} < .01$, and truth table class, $\underline{F}$ (3,66) = 19.3972, $\underline{p} < .01$.

Part (i) of Table 16 shows the mean proportion of errors within each truth table class summed across conceptual rule and IQ level. As can be seen in Part (i) of Table 16, subjects made the fewest number of errors in TT instances with errors increasing respectively for FF, TF and FT instances. Part (ii) of Table 16 shows the mean proportion of errors for each rule summed across truth table and IQ level.

No significant two-way interactions were revealed in the RL task condition. However,the three-way (IQ x Rule x Truth Table Class) interaction was significant, $\underline{F}$ (6,132) = 2.2965, $\underline{p} < .05$. Part (iii) of Table 16 shows the proportion of errors within each truth table class as a function of conceptual rule for the normal IQ group, while Part (iv) of Table 16 presents those figures for the superior IQ group.

In order to examine which differences contributed to the significant IQ x Rule x Truth Table Class interaction

Table 15

Rule Learning Task

2(IQ Level) x 3(Conceptual Rule) x 4(Truth Table Class) ANOVA

Summary for Truth Table Class Errors

Source	SS	df	MS	F
Between				
IQ	555.55	1	555.55	2.1684
Subjects (IQ)	5636.39	22	256.19	
Within				
Rule	6317.92	2	3158.96	14.1362**
IQ x Rule	940.33	2	470.17	2.1040
Subjects x Rule (IQ)	9832.50	44	223.47	
Class	12070.57	3	4023.52	19.3972**
IQ x Class	575.47	3	191.82	0.9248
Subjects x Class (IQ)	13690.21	66	207.43	
Rule x Class	1648.82	6	274.80	0.9806
IQ x Rule x Class	3861.44	6	643.57	2.2965*
Subjects x Rule x Class (IQ)	36992.40	132	280.25	

** $p < .01$

* $p < .05$

Table 16

Mean Proportion of Errors to Total Responses Within Truth Table Class for Subjects in the RL Task Condition

Part (i): Errors Summed Across Rules & IQ Level

Truth Table Class	TT	TF	FT	FF
Errors	3.85	18.53	20.08	11.07

Part (ii): Errors Summed Across Truth Table Class & IQ Level

Rule	Conjunctive	Disjunctive	Conditional
Errors	11.58	8.76	19.80

Table 16, cont.

Part (iii): Errors for Normal IQ

Rule	TT	TF	FT	FF
	Truth Table Class			
Conjunctive	4.50	19.67	11.58	6.33
Disjunctive	3.08	20.67	18.00	6.25
Conditional	7.83	21.83	39.42	18.08
	5.14	20.72	23.00	10.22

Part (iv): Errors for Superior IQ

Rule	TT	TF	FT	FF
	Truth Table Class			
Conjunctive	4.42	10.67	20.25	10.25
Disjunctive	0.00	11.75	7.58	2.75
Conditional	3.25	26.58	18.67	22.75
	2.56	16.33	17.17	11.92

Note. These figures represent the proportion of errors x 100.

revealed by this ANOVA, differences between truth table classes for each rule and differences between the rules for each truth table class were computed. These differences were computed separately for the two IQ levels.

For individual comparisons within subjects, the following correlated t formula may be used:

$$t - \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{(MS\ R \times TT \times S(I) \times 16}} \quad (2)$$

Where:

R = Conceptual Rule

TT = Truth Table Class

S(I) = Subjects within IQ level

Data for the correlated t computations are found in Parts (iii) and (iv) of Table 16. Using a two tailed test of significance, with alpha = .05, significant differences for normal IQ subjects were found for: the FT truth table class, conjunctive-conditional and disjunctive-conditional; for the conjunctive rule, TT - TF; for the disjunctive rule, TT - TF, TT - FT, TF - FF; and for the conditional rule, TT - TF, TT - FT, TF - FT, and FT - FF. All other comparisons for the normal IQ group were not significant.

For superior IQ subjects, significant differences were found for: the TF truth table class, conjunctive-conditional, disjunctive-conditional, and for the FF class, disjunctive-conditional; for the conjunctive rule, TT - TF, TT - FT, and TT - FF. All other comparisons for the superior IQ group failed to reach significance.

An additional 2 (IQ level) x 3 (conceptual rule) analysis of variance was performed on the dependent variable number of trials to criterion. Table 17 presents the summary of this ANOVA. As was the case in the AI task condition, subjects failing to reach criterion were assigned the maximum of 72 trials for purposes of this analysis. The ANOVA revealed a significant main effect of IQ level, F (1,22) = 9.06, $p < .01$, and a main effect of rule type, F (2,44) = 25,78, $p < .01$. There was also a significant IQ x rule interaction, F (2,44) = 7.66, $p < .01$. The mean number of trials to criterion as a function of IQ level and rule type are presented in Table 18. The figures in Table 18 represent both the main effects and, within the matrix, their interaction.

A simple main effects analysis on the number of trials to criterion revealed a significant effect of rule type for normal IQ subjects, F (2,44) = 29.48, $p < .01$; and for superior IQ subjects, F (2,44) = 3.95, $p < .05$. The simple main effect of IQ level was significant only for the conditional rule, F (1,66) = 23.20, $p < .01$.

Table 17

Rule Learning Task

2(IQ Level) x 3(Conceptual Rule) ANOVA

Summary for Number of Trials to Criterion

Source	SS	df	MS	F
Between	3626.61	23	157.68	
IQ	1058.00	1	1058.0	9.06**
Subjects (IQ)	2568.61	22	116.76	
Within	14658.67	48	305.39	
Rule	6815.20	2	3407.60	25.78**
IQ x Rule	2025.58	2	1012.79	7.66**
Subjects x Rule (IQ)	5817.89	44	132.22	
Total		71		

** $p < .01$

Table 18

Mean Number of Trials to Criterion

As a Function of IQ Level and Rule Type in the RL Task

	Conceptual Rule			
IQ Level	Conjunctive	Disjunctive	Conditional	
Normal	17.5	16.75	48.33	/ 27.53
Superior	20.42	13.00	26.17	/ 19.86
	18.96	14.875	37.25	

Note. Marginal column totals represent means for the main effect of rule type, while marginal row totals are means for the main effect of IQ level. Figures within the matrix represent the IQ by Rule interaction.

DISCUSSION

Bidimensional rule difficulty varied as a function of the type of rule (conjunctive, disjunctive or conditional) for almost all dependent measures in this study. The one exception to this effect was the criterion measure in the RL task condition. For that variable, the mean number of subjects failing to reach criterion was equivalent for the conjunctive and disjunctive rules and only slightly greater for the conditional rule. Aside from this exception, each dependent measure in both the AI and RL task conditions showed a significant main effect of conceptual rule type.

As revealed in several post hoc analyses, the main effect of rule was invariably due to the difficulty experienced by subjects in working with the conditional rule. In some cases, differences between the conjunctive and disjunctive rules also contributed to this effect. The difficulty of the conditional rule was consistent for both the AI and RL tasks.

In the AI task, the conjunctive rule was always either easiest or equal in difficulty to the disjunctive rule. In the RL task, this order was reversed, with the disjunctive rule always easiest or equivalent to the conjunctive rule. In other words, the obtained order of rule difficulty was consistent with each task type on all dependent measures. For the AI task, the rules were ordered, from easiest to most difficult: conjunctive, disjunctive, conditional. For the RL task, this respective order of difficulty was disjunctive, conjunctive, conditional.

Predictions made by use of the Sawyer and Johnson inference model of rule learning were generally supported by the results of the present study. Assuming that subjects approach the task with a pre-experimental bias favoring a conditional rule, the model predicts that subjects will perform best on the conjunctive rule, followed by the disjunctive rule, and then the conditional rule. In the AI task condition, this ordering of the rules was clearly evident. For the RL task condition, this predicted order was partially revealed in that the conditional rule was most difficult. The conjunctive - disjunctive order was reversed, however.

In as much as the quantification of the inference model is somewhat arbitrary (Salatas & Bourne, 1974), it could be argued that the expected differences between rules which are adjacent in difficulty might be negligible, while comparisons with non-adjacent rules are likely to be significant. Therefore, non-significant differences might be expected between the conjunctive and disjunctive rules. Further, these differences might reveal either ordering of the rules found in the present study.

Salatas and Bourne (1974) have expanded the Sawyer-Johnson model to include the compliments to the four primary bidimensional rules. When all eight rules are included in predictions of rule difficulty, the conjunctive and disjunctive rules are respectively ordered easiest and next to easiest, while the conditional and biconditional rules are next to most difficult and most difficult, respectively. Given the quantification of the model imposed by Salatas and Bourne (1974), the conditional rule is several steps removed from both the conjunctive and disjunctive rules. According to the logic developed here, the present study provides support for the Sawyer-Johnson model in both the AI and RL tasks.

For the most part, the results of the present study are consistent with the Sawyer-Johnson model. However, some difficulty remains in accounting for the reversal of conjunctive and disjunctive rule difficulty in the RL task with this model. It seems that a major source of difficulty in reconciling the present results with predictions from the Sawyer-Johnson model lies in the assumption that subjects approach the conceptual tasks with a conjunctive bias. In examining subjects' initial classification strategies, Dominowski and Wetherick (1976) found that about 58 percent of their subjects were using a strategy consistent with a disjunctive rule, while approximately 16 percent used a conjunctive strategy. Although they only examined a conditional rule and a negation rule, the results reported by Dominowski and Wetherick (1976) are significant to the present results in that they show that subjects may approach a rule learning task with a non-conjunctive bias.

In exploring a multibased expansion of the Sawyer-Johnson model, Reznick and Richman (1976) provide additional evidence that not all subjects have a conjunctive bias. Their research also shows that while the ordinal position of conjunctive and disjunctive rule difficulty reflects the subjects' bias, conditional rule difficulty is stable regardless of the pre-experimental bias of the subject. More important, in attempting to explain the reversal of conjunctive and disjunctive rule difficulty found between the AI and RL tasks in the present study, is Reznick and Richman's (1976) finding that subjects' pre-experimental bias may be affected by stimulus variables (such as the value of the relevant attributes), and that rule difficulty is easily altered by truth table class frequency and complexity. Given this lack of stability, and by extension of this finding, it seems likely that the present results reflect the sensitivity of subjects' initial bias to the demands of a particular task. In the present study, the AI task promoted a conjunctive bias, while the RL task elicited a disjunctive bias. This finding is also consistent with Taplin's (1975) suggestion, and the results obtained by Bourne and Guy (1968b) which indicate that rule difficulty is readily influenced by the processing demands of the particular conceptual task.

Overall, this study failed to reveal significant differences between the two IQ groups. Generally, however, in both AI and RL task conditions, superior IQ subjects revealed better performance than did normal IQ subjects on every dependent measure in the study. Differences between the two groups were negligible in both task conditions except for number of trials to criterion, where superior IQ subjects performed significantly better than did the normal IQ groups on both AI and RL tasks (see Tables 11 and 18).

It was suggested that there might be differences between normal and superior IQ groups on pre-experimental bias. There was no evidence in the present study to provide support for this suggestion in either task condition. The order of rule difficulty was the same for IQ groups on all dependent measures.

One of the major areas of focus in the present study was performance differences between IQ groups as a function of rule difficulty. The expectation that differences between IQ levels would increase as rule difficulty increased was supported in the RL task condition, where subjects in the superior IQ group showed significantly fewer trials to criterion than normal IQ subjects on the conditional rule (see Table 18).

Although there were no other significant effects of IQ in the RL task, the data on statement of the correct hypothesis were in the expected direction (see Table 13). On the disjunctive rule (easiest), there were no differences between IQ groups. For the conjunctive rule (next to easiest), a slight difference favoring the superior IQ group was obtained. On the conditional rule (most difficult), the differences favoring the superior IQ group were even greater.

Results in the AI task run counter to the prediction that differences between IQ groups will increase as a function of rule difficulty. For proportion of errors to total responses, collapsed across truth table class, the IQ level by rule interaction shows fewer errors for the normal IQ group than for the superior IQ group on the conditional rule (see Table 8).

A similar result was obtained for statement of the correct hypothesis on the conditional rule in the AI task (see Table 5). For this dependent measure, subjects in both IQ groups stated the correct hypothesis for the conjunctive rule. For the disjunctive rule, all superior IQ subjects stated the correct hypothesis, while 33 percent of the normal IQ subjects in this condition failed to state the correct hypothesis. For the conditional rule, 58 percent of the subjects in the superior IQ group and 42 percent of the normal IQ subjects failed to state the correct hypothesis. As mentioned above, this result is responsible for the IQ by rule interaction on this measure. However, the simple main effects analysis shows that the significant difference between IQ groups was on the conjunctive rule, not the conditional rule, and this difference is in the predicted direction.

In the AI task, the crossover between normal and superior IQ groups on proportion of errors is not as easily dismissed as is the crossover on statement of the correct hypothesis. For proportion of errors, the greatest difference between IQ groups is evidenced on the conditional rule, where subjects in the normal IQ group performed better than superior IQ subjects. Why this is the case is not readily ascertained from the data. One subject in the normal IQ group did not make any errors in this treatment condition, but this does not account for the crossover. An examination of truth table class errors reveals no major differences between IQ groups which would help explain this result. It remains for further research to examine this particular condition before some explanation is to be found.

The present study also examined truth table classification strategies between IQ groups in both AI and RL tasks. Based on analysis of errors within truth table classes, this effect is consistent with the Sawyer-Johnson model of rule difficulty and truth table problem solving strategy, in that TT and FF instances were both easier than TF and FT instances (see Table 16). This result was consistent for both IQ groups.

It was expected that superior IQ subjects would acquire a truth table problem solving strategy more rapidly than normal IQ subjects and that this would be evident in different error rates within truth table classes for the two IQ groups. This expectation was not confirmed, although it was not contradicted in the present study. That is, the results were generally in the predicted direction in the RL task. Additionally, superior IQ subjects revealed fewer significant differences in error rates between the truth table classes than did normal IQ subjects. This means that, as truth table classification became more difficult, the normal IQ group did not perform as well as the superior IQ group.

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In general, for the RL task, the present results for truth table class errors are consistent with previous findings. Dominowski and Wetherick (1976) predicted that TT and FF classes should be easier than TF and FT classes, given their results in examining classification bias. The results of the present study provide support for this prediction for both IQ levels and all three rules. In the AI task condition, no such regularity was obtained. This is reflected in the lack of a significant main effect of truth table class, which argues against the proposition that subjects may acquire a truth table problem solving strategy in AI tasks. If an extension of the truth table problem solving model was appropriate for AI tasks, it would be expected that error rates for TT stimuli would be the same or similar for all three rules since they are like (i.e., all positive) instances. Also, for FF stimuli, error rates should be similar for the conjunctive and disjunctive rules (where FF instances are negative) and greater for the conditional rule, where FF stimuli are positive. As Table 9 clearly shows, however, this result was not obtained in the present study.

The present results for the AI task do not conform to predictions from any model which examines the effects of subjects' classification bias and problem solving strategy. Although future research may shed some light on this, at present, it can only be concluded that there is no evidence supporting the suggestion that subjects may acquire a consistent truth table problem solving strategy in attribute identification tasks. At the very least, this study suggests that the quantification of the Sawyer-Johnson model for rule difficulty and truth table strategy cannot be extended to AI problems. This holds for the model as expanded by Salatas and Bourne (1974) and for the multibiased modifications suggested by Reznick and Richman (1976).

Rejection of the hypothesis of homogeneity of variance between AI and RL task conditions indicates that there are significant differences between the two types of task. This supports previous contentions that the processing required by AI and RL tasks is not the same (Bruner, et al., 1956; Salatas & Bourne, 1974; Taplin, 1975). Regardless of differences in processing demands between AI and RL tasks, the conditional rule form is consistently more difficult than either the conjunctive or the disjunctive rules. This latter conclusion is supported by the difficulty experienced by all subjects in the present study during the training phrase of the experiment. Whereas all subjects were able to respond correctly in the card sorting task for the conjunctive and disjunctive rules, the conditional rule presented considerable difficulty for all subjects.

In light of these findings, it seems that although the Sawyer-Johnson model may account for rule difficulty in both AI and RL tasks, separate models may be required to explain subjects' problem solving strategies in the two types of tasks. Truth table responses may not be an appropriate dependent measure for AI tasks. On the other hand, the consistent ordering of rule difficulty for all dependent measures within each type of task indicates a close relationship between subjects' statement of hypotheses, error rates, and number of trials required to reach criterion for learning both AI and RL tasks.

One of the major foci of the present study was the relative performance of the two IQ groups. In general, predictions regarding differences between normal and superior IQ subjects were not contradicted in the present study. At the same time, however, the IQ factor was not revealed as significant a variable as was expected. There are several possible reasons for this apparent lack of difference between normal and superior IQ.

It is possible that the small number of subjects in each cell (n = 12) failed to produce reliable differences of a great enough magnitude to be detected in the present study. The small but fairly consistent differences observed between IQ levels lends some support to this interpretation. Along similar lines, it is possible that the small sample used in this study was a fairly homogeneous group. This would have the effect of reducing the reliability of predicting differences between subjects assigned to the two groups (Anastasi, 1976).

Given the type of design used in the present study, another possible explanation of the lack of a significant main effect of IQ is provided by Winer (1971). He points out that the main effect of IQ is confounded with differences between groups of subjects nested under the IQ factor. The effect of this confounding is to lower the sensitivity of the test due to a greater number of uncontrolled sources of error variance. Winer (1971) also notes that when there is a positive and constant correlation between pairs of measurements, the error term for the between subjects variable will be greater than that for within subject variables.

In the present study, there is some evidence of such a positive and constant correlation between the IQ factor and spurious differences between groups not due to IQ per se. This correlation is seen in the consistency with which the error terms for the between subjects variable is greater than for the within subjects variable. Although this does not mitigate entirely the lack of significant main effects for IQ level, it does argue for further consideration of the IQ variable in studies of conceptual learning. The suggestion here is that future research should employ an alternate design which would include a covariate which would statistically absorb a portion of the variance in the between subjects error term (Winer, 1971).

One additional explanation for the lack of a significant IQ effect is the possibility that the training procedure may have reduced the differences between IQ groups. It was previously mentioned that subjects had some difficulty in learning to respond successfully on the card sorting task. During that phase of the experiment, subjects had particular difficulty with the conditional rule. Bourne and Guy (1968a) have observed strong transfer effects, particularly when subjects are trained with a conditional rule which focuses on responding to TF and FT stimuli and on classifying FF instances as positive. Furthermore, training, even without such a focus, may result in changes in strategy from those of the naive subject (Bourne, 1970; Bruner, et al., 1956). In light of this possibility, when training procedures are used, it might be fruitful in future research to examine group differences in the number of practice trials necessary for basic understanding of the various rules.

This study has examined the role of individual differences in conceptual behavior and problem solving.

Although the magnitude of the IQ group differences was often not statistically significant, general support for the existence of IQ group differences in conceptual behavior has been provided. At the very least, this study argues for continued investigation in the area. Consistent differences between the conditional rule and the conjunctive and disjunctive rules have been found in both AI and RL tasks. Support was also found for the acquisition of a truth table problem solving strategy for both IQ groups in the RL task, although this type of problem solving strategy was not evidenced in the AI task.

Lastly, this study also shows that it is both possible and desirable to examine the relation of IQ and the conceptual abilities with which it is typically associated.

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APPENDIX A

APPENDIX A

Instructions

Phase One

"There will be two parts in this experiment. In the first part, you will be given four tests which are taken from the Wechsler Adult Intelligence Scale. Performance on these tests will be used as a measure of general intelligence, for purposes of comparing groups of subjects who will be participating in this experiment. The results from these tests will not be used for any other purpose and you cannot be identified individually. Professional ethics prevent the Experimenter from revealing the results of these measures and you will not be given any information on this phase of the experiment. Do you have any questions?

Phase Two

In the second part of this experiment, you will be asked to solve several problems. In solving these problems, it will be necessary for you to form and use concepts. A concept is an idea, acquired through experience, which enables us to "zero-in" on the properties or qualities of things that are meaningful, while ignoring the properties or qualities of things which are unimportant.

The Experimenter has placed a list of the properties and qualities of the materials which we will be using on the table in front of you. As you can see, there are four properties or dimensions, each having three qualities or values.

1) The Number of Figures: one, two, three

2) The Shape of the Figures: circle, square, triangle

3) The Color of the Figures: red, blue, green

4) The Shading of the Figures: open, diagonal, cross hatched

Each stimulus card will have a combination of one value from each of the four dimensions. There are 81 different possible combinations of this sort.

The Experimenter has placed three examples of stimulus cards on the table in front of you. As the example cards show, one value from each dimension will be represented on each card. Between the three example stimuli, you can see all possible values from each dimension.

1) One, Blue, Square, Cross Hatched

2) Two, Red, Circle, Diagonal

3) Three, Green, Triangle, Open

Each of the concepts that you will be learning will be based on only two of these values. For example: "one," blue." In this case, one, blue are the two important qualities or values, and all other values are unimportant to the concept. However, this is only part of the information that you will need to solve the problem.

The other part of the information that will be necessary is the way in which these values are related. With two-valued concepts, there are several relationships or rules of combination which can be used. We are going to be concerned with four of these rules. The Experimenter has placed on the table in front of you a list of the four rules which we will be using. Using "A," "B" as the two important values, these rules are:

1) Conditional: IF A THEN B

2) Disjunctive: A OR B

3) Conjunctive: A AND B

4) Biconditional: IF A THEN B AND IF B THEN A

For each stimulus you will be required to say either "yes" or "no" depending on whether or not you think the stimulus presented is a member of the concept group. Remember that the concept will depend on both the rule and the two important values. Following the previous example of "ONE, BLUE," your response would be "yes" if the conditions are met as follows for each rule:

Conditional: IF the stimulus has ONE figure THEN it must be BLUE.

Disjunctive: IF the stimulus has EITHER ONE figure OR it is BLUE

Conjunctive: IF the stimulus has BOTH ONE figure AND it is BLUE

Biconditional: IF the stimulus has ONE figure THEN it must be BLUE AND IF the stimulus is BLUE THEN it must have ONE figure

In order to help you understand these rules, you will practice by sorting ordinary playing cards according to each of the rules. For practice purposes, let us say that the playing cards have two dimensions, with two values each: Color (red, black) and Shape (face card, numbered card). Aces will not be used. For the practice problems you will be told both the rule and the two important values. Your task is to sort the cards into two categories, those which are members of the concept group, and those which are not. You may refer to the rule definition sheet which has been provided. Do you have any questions?

For your first practice problem, the important values are Red, Numbered Card. For each card, respond by saying either "yes" or "no," using a Conditional Rule.

For the second practice problem, the important values are Black, Face Card. For each card, respond using a Conjunctive Rule.

For the third practice problem, the important values are Red, Face Card. For each card, respond using a Biconditional Rule.

For the fourth practice problem, the important values are Black, Numbered Card. For each card, respond using a Disjunctive Rule.

Rule learning instructions: For the problems you will now be given, you will be told only the two important values. Your task will be to discover the rule which defines the relationship between the two values. In order to prevent you from anticipating the correct rule, it will be chosen randomly from the four rules and then replaced. In this way, any one of the four rules could be the correct rule on any problem.

The Experimenter will show you a series of cards, one at a time. For each card, respond "yes" if you feel the important values exist in the correct relationship. If you think the important values do not exist in the correct relationship, you should respond "no." The Experimenter will record your responses and tell you if the stimulus is actually a member of the correct group or not by saying "yes, it is" or "no, it is not." After the series is complete, the Experimenter will ask you to name the rule which defines the correct relationship between the important values.

Because you will not know which of the four rules has been selected for this concept, your responses to the first few stimulus cards will only be guesses. But, after discovering the correct responses to the stimulus patterns, you will soon gain enough information to use the concept that has been selected correctly. There is no penalty for the wrong response and no reward for the correct response. What is important is that you eventually discover the rule which defines the correct relationship between the important values. Try to be right as often as you can, and, just as importantly, try to gain as much information as you can about the concept from eacl pattern. Feel free to refer to the list of dimensions or the rule definition sheet if necessary.

Do you have any questions?

Attribute identification instructions: For the problems you will now be given, you will be told only the rule which defines the relationship between the two important values. Your task will be to discover which two values are important. The rule will be chosen randomly from the four rules and then replaced. In this way, any one of the four rules could be used (any problem, and you will be told which rule has been chosen.

The Experimenter will show you a series of cards, one a time. For each card, respond "yes" if you feel that the car(has the important values in the relationship defined by the rule. If you think that the card does not have the important values in the relationship defined by the rule, you should respond "no." The Experimenter will record your responses and tell you if the stimulus is actually a member of the concept group or not, by saying "yes, it is" or "no, it is not." After the series is complete, the Experimenter will ask you to identify the two important values which make up the concept.

Because you will not know which are the two important characteristics, your responses to the first few stimulus cards will only be guesses. But, after discovering the correct responses to the stimulus patterns, you will soon gain enough information to use the concept that has been selected correctly. There is no penalty for the wrong response and no reward for the correct response. What is important is that you eventually discover the two values which make up the concept. Try to be right as often as you can, and, just as importantly, try to gain as much information as you can about the concept. Feel free to refer to the list of dimensions or the rule definition sheet if necessary.

Do you have any questions?

Random selection instructions: [The following procedure was repeated for all subjects prior to each problem]. For each problem, the conceptual rule will be chosen at random. In order to do this, the Experimenter has assigned one of the four conceptual rules to each of these four Aces. You are to pick one of the four cards and the rule which has been assigned to that card will be the chosen rule for this problem. Do not take the card from the Experimenter and do not look at the card. Simply indicate the card the Experimenter should use by pointing to the card. [In the AI task condition, the subject was then informed which rule had been chosen. In the RL task condition, the subject was then informed which two stimulus values would be relevant].

APPENDIX B

APPENDIX B

Stimulus Dimensions

DIMENSIONS	VALUES		
Number of Figures:	ONE	TWO	THREE
Shape of Figures:	CIRCLE	SQUARE	TRIANGLE
Color of Figures:	RED	BLUE	GREEN
Shading of Figures:	OPEN	DIAGONAL	CROSS HATCHED

APPENDIX C

APPENDIX C

Rules Definitions

Conditional:	IF A THEN B
Disjunctive:	A OR B
Conjunctive:	A AND B
Biconditional:	IF A THEN B, AND IF B THEN A

APPROVAL SHEET

The thesis submitted by Donald E. Raney has been read and approved by the following committee:

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The final copies have been examined by the director of the thesis and the signature which appears below verifies the fact that any necessary changes have been incorporated and that the thesis is now given final approval by the Committee with reference to content and form.

The thesis is therefore accepted in partial fulfillment of the requirements for the degree of Master of Arts.

September 4, 1981
Date

Frank Slaymaker
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