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ABSTRACT

This investigation compares overt judgments about tenable hypotheses to choices in a concept identification task, as a function of stimulus similarity on successive trials. Two mathematical models are tested: (a) A 1-element local consistency version of Restle's concept identification model and (b) the same model with two additional passive states in which hypothesis testing does not occur. Both models successfully predict a decline in percent correct choices from Trial 1 to Trial 2 in one group. The only notable difference between the predictive characteristics of the two models is that only the former model has a tendency to predict zero occurrences of certain response sequences which do actually appear. Three hypothesis judgment strategies were investigated, Cumulative Deductive strategies being dominant early in training and Cumulative Concrete strategies being dominant midway in training. A finding by Berger that the most frequent error in processing information is the failure to eliminate a hypothesis when it is contradicted by feedback on the current trial was confirmed. (Author)

Effects of Stimulus Congruence
on Hypotheses Held
in a Concept Identification Task[1, 2]

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Abstract

This investigation compares overt judgments about tenable hypotheses to choices in a concept identification task, as a function of stimulus similarity on successive trials. Two mathematical models are tested: (a) A 1-element local consistency version of Restle's concept identification model and (b) the same model with two additional passive states in which hypothesis testing does not occur. Both models successfully predict a decline in per cent correct choices from Trial 1 to Trial 2 in one group. The only notable difference between the predictive characteristics of the two models is that only the former model has a tendency to predict zero occurrences of certain response sequences which do actually appear.

Three hypothesis judgment strategies were investigated, Cumulative Deductive strategies being dominant early in training and Cumulative Concrete strategies being dominant midway in training. A finding by Berger that the most frequent error in processing information is the failure to eliminate a hypothesis when it is contradicted by feedback on the current trial was confirmed.

Effects of Stimulus Congruence
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Berger (in press) has reported a number of instances in which hypothesis judgments contradict a particular hypothesis theory of concept identification. For example, a hypothesis held on one trial may be inconsistent with feedback on that trial and yet may be retained on the next trial (failure of the "lose-shift" assumption). The present study attempts to confirm in general the Berger findings while providing other evidence from choice responses concerning the adequacy of the Restle (1962) 1-element model with local consistency (Gregg & Simon, 1967; Cotton, in press) and a new model which assumes that at the beginning of a problem most subjects respond randomly rather than selecting and processing hypotheses. The concept identification task employed was an affirmative one, i.e., one with the solution depending on the values of only one dimension.

A further feature of this experiment is that two groups with different degrees of stimulus similarity from trial to trial are compared. Let stimulus congruence (i) on Trial n be defined as the number of hypotheses consistent with stimuli and feedback for both Trial n-1 and Trial n. Then one condition in the present study has $i = 1$, and the second has $i = 2$. Hypothesis theory implies that a smaller proportion of correct choices will be made in presolution trials for $i = 1$ than for $i = 2$. This prediction has been confirmed within a series of trials for single group and between groups for a single trial (Cotton, 1971). The present study tests the prediction for several trials, with different groups having different i

values. Because a pretraining procedure very similar to the final task was used, it may be predicted that Trial 1 performance will be quite high, with a decline on Trial 2 occurring for the $i = 1$ condition in view of the theoretical implication just noted.

Method

Subjects and Apparatus

Fifty UCSB students, volunteers from lower division psychology courses, served as experimental subjects. These 50 were randomly assigned to two groups of 25 each. One subject was run at a time. Stimuli were presented with a Carousel projector, using a 5 sec. exposure time for each test stimulus or feedback stimulus. Stimuli were viewed on a beaded screen, with projection from a position beside the subject.

Practice Problem

Subjects saw an "E" or an "R," either in upright or sideways position and either in upper case or lower case form on each trial and received feedback of "1" or "0," depending upon whether the letter was upright ("1") or sideways ("0"). The subject was required to press a button marked "1" or a button marked "0" while the test stimulus was present, before feedback for that trial was presented. Thus this was a 3-dimensional binary task with the position of the letter being the relevant dimension and its case and particular position in the alphabet being the irrelevant dimensions. Eight trials with this practice problem were given each subject. Stimulus orders were random and unrestricted, with different orders being used for each subject. At the beginning of the experiment subjects were fully informed about the six possible one-dimensional hypotheses constituting potential solutions to the problem.

Experimental Problem

The stimuli for this problem were just as in the practice problem except that the letters used were "A" and "B." The same solution as before was employed. Each subject received four trials on this problem, with feedback after each choice response. After feedback for each of the first three trials, a slide was presented asking, for each of the three dimensions, whether either possible pairing of dimension value and choice appeared to be correct, or whether there was not enough information yet about that dimension ("NEI"), or whether it appeared not to be relevant ("NR"). The time allotted for these judgments was approximately 30 sec. These judgments were made orally by the subject and recorded in writing by the experimenter.

Stimulus Sequences for the Experimental Problem

For each Group 1 member a different sequence of stimuli was selected. The Trial 1 stimulus was selected at random from the eight possible values. On Trial 2 the stimulus presented was assigned at random from the two stimuli for which $i = 1$. For example, if "A" (in upright position) were the Trial 1 stimulus, the Trial 2 stimulus was either "b" or "<" since these were the only stimuli which confirmed the correct hypothesis ("up = 1 and sideways = 0") on both trials and confirmed no other hypothesis for both trials. On Trial 3 Group 1 members were randomly assigned one of the two stimuli for which $i = 1$ when compared to the Trial 2 stimulus. The same rule held for Trial 4. It may be seen that no subject in Group 1 could receive any stimulus outside a specific set of four implied by the Trial 1 stimulus and the $i = 1$ condition.

Group 2 stimuli were selected just as for Group 1, except that on Trial 2 and thereafter $i = 2$, yielding four possible stimuli for any trial after Trial 1, with any one of the eight stimuli being possible sometime after Trial 1 even though there were only four possible options for any subject on any single trial except Trial 1.

Results

Two kinds of data will be analyzed in this section: (a) Choice of "0" or "1" responses on each of the four feedback trials ("FT's") and (b) judgments of the relevance of each dimension (and, if judged relevant, the direction of pairing of dimension values and hypothesized correct responses to those values) following the first three feedback trials.

Relations of Choice Responses to Prior Feedback and Choice Responses

Table 1 indicates that each group showed a general increase in proportion of correct responses as a function of FT number. The mean numbers of

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Insert Table 1 about here

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total errors per person are 1.20 for Group 1 and 1.04 for Group 2. Except on Trial 2, where the proportion correct is substantially lower than for Group 2, the two groups' trial by trial trends are very similar.

Two models have been used in an attempt to fit the choice data of this experiment. First, the Gregg and Simon local consistency version of Restle's (1962) 1-element hypothesis model has been used to predict the relative frequencies of all 16 possible sequences of correct and incorrect responses on FT1 through FT4. Because of the nonrandom nature of the sequences of stimuli in the two experimental groups, these predictions were based on Eqs. 21 and 22 of Cotton's (in press) sequence-specific

(Level 2 in his terminology) version of this model, plus Eq. 2 (below) of the present paper.

The curve-fitting procedure was to use the Chandler (1969) Stepit computer search program to estimate parameter values ($\hat{c} = .1863$ and $\hat{p} = .4846$) in such a way as to minimize the sum of squared errors (Σe^2) of prediction of the 16 relative frequencies just mentioned, totaling squared errors across the two groups as well as the 16 sequences for each group. Table 2 presents a comparison of obtained and predicted results for this model as well as for the one to be discussed shortly.

Insert Table 2 about here

Some indication of the reason for the obtained parameter estimates for the 1-element local consistency model should now be given. Suppose that we call the correct hypothesis H_1, its complement H_2, and the hypotheses based on irrelevant dimensions H_3 through H_6. It is convenient to define an initial vector for these hypotheses as follows:

$$\begin{array}{lcccccc} & H_1 & H_2 & H_3 & H_4 & H_5 & H_6 \\ \underline{P}_1^* = [& 1/6 + \varepsilon, & 1/6 - \varepsilon + 4\delta, & 1/6 - \delta, & 1/6 - \delta, & 1/6 - \delta, & 1/6 - \delta]. \end{array} \qquad (1)$$

Because the practice task had the same solution as the experimental problem, an assumption of an ε greater than zero seems reasonable. One would also expect δ to exceed zero, but this does not happen here.

Equation 1 can be modified to yield probabilities for being in the conditioned state (C), error state (E), and chance success state (S) as follows: H_1 is State C; its probability may be written either as c or as $1/6 + \varepsilon$ as in Eq. 1. Assuming that all stimuli are equiprobable on Trial 1, the probability of a chance success is one-half the sum of the probabilities for H_3 through H_6, or $1/3 - 2\delta$. This probability may also be called $(1-c)p$, yielding $\delta = 1/6 - \frac{1}{2}p(1-c)$. By subtraction, the probability of being in the error state on Trial 1 is $1/2 - \varepsilon + 2\delta = (1-c)(1-p)$. Thus

$$\underline{P}_1 = \begin{array}{ccc} C & E & S \\ [c, & (1-c)(1-p), & (1-c)p]. \end{array} \tag{2}$$

Note that the values of $\hat{c}$ and $\hat{p}$ given previously imply that $\hat{\varepsilon} = .0196$ and $\hat{\delta} = -.0305$. This empirical fit yields an extraordinary value for the $\underline{P}_1^*$ vector:

$$\underline{P}_1^* = \begin{array}{cccccc} H_1 & H_2 & H_3 & H_4 & H_5 & H_6 \\ [.1863, & .0251, & .1972, & .1972, & .1972, & .1972], \end{array}$$

suggesting that the principal effect of pretraining with a task having the same solution as the experimental task is to weaken the complement of the correct hypothesis.

Because the 1-element local consistency model just considered was unsatisfactory in its prediction of zero probabilities for three response sequences which actually occurred, a new model was devised and tested: In addition to the three states of the previous model, let there be two passive states in which a person is correct or incorrect on the basis of chance alone rather than because of the hypothesis he holds. Let it further be assumed that once a person leaves the pair of passive states he begins to select hypotheses and conform to the 1-element local consistency model. It will be convenient to assume the following initial vector:

$$\underline{P}_1 = \begin{array}{ccccc} C & E & S & G- & G+ \\ [c & 0 & 0 & d & 1-c-d] \end{array} \tag{3}$$

where G- and G+ are passive states in which errors and correct responses, respectively, are made, c is the probability of being in State C initially, and d is the probability of being in State G- initially. The transition matrix for an experiment with K dimensions (3 in this case) and congruence value i on every trial after the first will be:

$$\underline{T} = \begin{array}{c} \\ C \\ E \\ S \\ G- \\ G+ \end{array} \begin{array}{c} \begin{array}{ccccc} C & E & S & G- & G+ \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1/K & \frac{K-i}{K} & \frac{i-1}{K} & 0 & 0 \\ 0 & \frac{K-i}{K-1} & \frac{i-1}{K} & 0 & 0 \\ \frac{1-f}{K} & \frac{(1-f)(K-i)}{K} & \frac{(1-f)(i-1)}{K} & \frac{f}{2} & \frac{f}{2} \\ \frac{1-f}{K} & \frac{(1-f)(K-i)}{K} & \frac{(1-f)(i-1)}{K} & \frac{f}{2} & \frac{f}{2} \end{bmatrix} \end{array} \qquad (4)$$

where f is a parameter representing the probability of staying in some passive state on the next trial, given that one is already in such a state. A Stepit search for the purpose of minimizing the squared errors of prediction, just as before, yields the entries in Tables 1 and 2 for the passive state model. The parameter estimates prove to be $\hat{c}$ = .0045, $\hat{d}$ = .4151, and $\hat{f}$ = .1577. It may be noted that no pair of predictions in Table 2 for a given response pattern but a pair of theories differ by more than .014; no pair of predictions in Table 1 differ by more than .036. Furthermore, Σe^2 = .111 for the 1-element local consistency model, and Σe^2 = .110 for the passive state model. Thus the models give almost identical results. However, the passive state model serves its intended purpose by yielding no false predictions of zero frequency for any response pattern.

Analysis of Hypothesis Data: Predictions from Feedback History

Table 3 presents the proportion of persons judging that a specific

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Insert Table 3 about here

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dimension is relevant on each trial. The proportion of persons saying that the relevant dimension is "upright versus sideways" increases with practice, as desired. Because in Group 1 the solution is logically implied by the end of Trial 2 and in Group 2 by the end of Trial 3 (except for three subjects where two hypotheses remained tenable at the end of Trial 4), we would expect a larger proportion of relevant judgments to the "upright versus sideways" dimension for Group 1 than for Group 2 immediately after Trial 2. This was indeed found. However, a more striking difference between groups appears after Trial 2 for the "capital versus lower case" dimension.

A further analysis of the judgments of dimensional relevance asks the relative frequency of judgments which could be generated by different information processing strategies. For example, a strict deductive strategy would conclude after Trial 1 that one does not know which dimension is relevant, so that NEI responses would be assigned to each dimension. A cumulative deductive strategy over all trials to date leads to assigning NR to each irrelevant dimension and "Up = 1" to the relevant dimension after Trial 2 of Group 1.

A scoring procedure has been developed which assigns one point whenever a particular dimension is treated cumulatively and deductively after a given

FT. Thus from 0 to 3 points are assigned to each subject on each trial as his cumulative deductive score. The maximum total points in a group of 25 subjects becomes 75 per trial.

A second, but ultimately unwise strategy is to assert that all hypotheses confirmed on a given trial will be confirmed on the next. This current feedback strategy can also be scored from 0 to 3 on each trial, depending upon how many dimensions are assigned hypotheses consistent with current feedback.

A third strategy for making dimensional judgments will be called cumulative concrete[3]: with this strategy subjects combine parts of the first two strategies, using current feedback except when the cumulative deductive strategy shows a dimension to be irrelevant, in which case the dimension is judged NR. Again the possible scores per person per trial are 0 to 3.

Table 4 shows the proportion of hypothesis judgments consistent with each strategy following each FT for each group. Immediately after Trial 1

Insert Table 4 about here

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the deductive strategy is more popular than the others for each group (meaning that NEI judgments were frequent), and the current feedback strategy was least frequent for each group after Trials 2 and 3 (meaning that information from more than one trial was being used). Immediately after Trial 1 the treatment of the two groups is differentiated logically and procedurally. However, the cumulative concrete and cumulative deductive strategies are experimentally forced to be equivalent for Group 1 following Trials 2 and 3; this is reflected in Table 4. This equivalence is not true for Group 2.

Relations of Hypotheses to Previous Hypotheses and to Feedback History

As noted earlier, Berger (in press) has provided a classification of kinds of processing errors, if any, which occur in the assignment of hypotheses after each FT. The same eight error types used in interpreting his SC (single cue) test data are used here. Additional categories of error are necessitated by the present NEI response option.

The rationale for these additional error categories depends on a clear specification of correct processing. Note that Berger's "not sure" classification and the present NEI (not enough information) are not logically equivalent. We will define "correct processing" in such a way that Berger's usage is maintained or nearly maintained at the same time that subjects are allowed to use either the cumulative concrete or cumulative deductive strategy without being penalized for them. The following five principles are invoked:

(a) An NR response immediately after FT1 is a processing error because NR cannot be logically inferred from a single feedback trial; similarly a specific hypothesis contradicting feedback on FT1 is an error.

(b) Once a specific hypothesis is reported, it is a processing error to change to another hypothesis, to NEI, or to NR if the FT just before the change is consistent with that specific hypothesis. It is also a processing error not to change to NR if an FT just before a hypothesis judgment contradicts the hypothesis formerly held about a particular dimension.

(c) Once NR is reported, it is a processing error ever to change to NEI or to a specific hypothesis. (Of course, if NR were falsely reported at first, a change away from NR would be necessary before solving the problem; the shift is arbitrarily called a processing error because, if a dimension is irrelevant at one stage of training, it will be irrelevant ever after in the present study.

(d) Once NEI is reported, it is a processing error not to change to NR as soon as two successive FTs have supported opposite hypotheses for that dimension. If misprocessing of this kind has occurred, it is a further processing error not to change from NEI to NR on the next opportunity thereafter or any subsequent opportunity.

(e) Once NEI is reported, it is a processing error not to shift to a specific hypothesis once all other possible hypotheses have been logically eliminated by FTs. An earlier shift to a specific hypothesis is permissible if all previous FTs are consistent with that hypothesis.

The scoring principles just stated imply that a perfect processor not only has the mechanisms available which are required for following a win-stay, lose-shift strategy but also has a tally and retrieval system by which he records and retrieves, for each trial, which possible hypotheses were and were not supported. For the sake of specificity in scoring we say that false hypotheses are nonetheless assumed to be accompanied by correct tallies, permitting the second sentence of (d) to apply. Note that a processing error may lead to a correct response, as when one shifts from a false NR for the relevant dimension to the correct hypothesis. It seems reasonable to suppose that the false NR resulted from a mistally; else it should have been corrected as in the second sentence of (d).

Table 5 shows that the most frequent processing error in each group of

Insert Table 5 about here

the present study, as well as in Berger's study, was the failure to make an NR (not relevant) judgment when logically required. Similarly, the least frequent error per group of the eight possible in both experiments was a shift from NR to a hypothesis inconsistent with current feedback. In 61.33% of hypothesis judgments for Group 1, one of the 11 processing errors occurred; in 26.17% of the judgments for Group 2, one of these errors occurred. This difference appears to reflect failure to shift to NR for irrelevant dimensions and to the correct hypothesis for the relevant dimension on Trial 2, Group 1, where the solution was logically implied.

Relation of Choice Responses to Previously Held Hypotheses

Use of a specific hypothesis theory to predict choice behavior from hypothesis data or vice versa is complicated in the present experiment by the fact that subjects were asked to judge the relevance of each stimulus dimension but not to state a single working hypothesis or to state a judgment about the direction of a dimension's pairing with correct hypotheses when NEI responses were made. Thus nothing comparable to the listing of hypotheses in a focus sample (Trabasso & Bower, 1968) or in the subset still under consideration (Chumbley, 1969; Restle, 1962) is available for analysis. Whereas a deductive strategy after FTI would have led all dimensions for each group to be classified NEI, a forced choice with each dimension would have led to a focus sample like (but not identical to) that expected with one of the multi-element models just mentioned. Forcing a further statement of the working hypothesis to guide the response on the next FT would also have helped to relate these data to existing multi-element models. In the absence of such additional data the present analysis must ask whether choice responses are consistent with some working hypothesis which could reasonably have been generated in the light of current trial feedback and existing dimensional judgments.

Some very general implications of conventional hypothesis theory are that: (a) if only one hypothesis is held after feedback on one trial, the next choice response should be consistent with that hypothesis; (b) if two or more hypotheses are held after feedback on a trial, the next choice response must be consistent with at least one of those hypotheses; and (c) if no hypothesis is held after a given feedback trial, any choice response on the next trial is acceptable, regardless of whether that response is consistent with the immediately preceding feedback. Condition (b) is sometimes satisfied because of stimulus properties rather than behavioral laws: For example, since the stimulus "B" can only lead either to a choice of "1" or a choice of "0," regardless of what hypotheses are held, it is no confirmation of theory to say that, if a subject believes "aye = 1" and "up = 1," the fact that the "0" response to "B" is consistent with the former hypothesis and a "1" response to "B" is consistent with the latter is hardly evidence for hypothesis theory. Similarly (c) will always hold. Therefore, (a) is most important, with (b) being crucial only for a stimulus such that all hypotheses held on the previous trial imply the same response on the next trial. Table 6 attempts to test the adequacy of

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Insert Table 6 about here

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hypothesis theory by reporting how many subjects whose hypothesis or hypotheses at each stage of training all imply the same response make a choice response (or fail to make such a response) consistent with their hypothesis report. Remembering that many subjects are ignored because of the problem just noted with implication (b), we conclude that less than half of the remainder (.478) conform to theory after FT1, with this proportion growing to .874 after FT3, for the two groups combined. This is a poor showing for hypothesis theory.

Discussion

The present experiment shows moderate conformity of choice behavior to mathematical predictions from two hypothesis theories. The most striking success of these models was the ability of each to predict a decline from Trial 1 to Trial 2 in Group 1, because of the low chance probability of selecting a correct response when i = 1. The passive state model has two advantages over the 1-element local consistency model: (a) It does not predict zero probability for any response pattern, thus preventing gross contradictions of a kind common to the latter model. (b) The passive state model implies that hypotheses are not often controlling choice behavior early in training, thus making the prior Trial 2 and Trial 3 conformity of choice behavior and verbalized hypotheses (Table 6) more consistent with theory.

Hypothesis judgments seem only moderately consistent with hypothesis theory. The information processing which occurs during hypothesis judgment is less rational than theory predicts. This suggests that hypothesis theory must either be drastically revised or that verbalized hypotheses be considered to conform to quite different theories than the entities previously postulated in hypothesis theory.

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Footnotes

1. This research was supported by the Biomedical Sciences Support Fund of the U. S. Public Health Service and by the Research Committee of the University of California, Santa Barbara.

2. The assistance of Mary Libbey Conley in performing this experiment and of Dr. Dennis Ridley in performing early data analyses is gratefully acknowledged.

3. The cumulative deductive and cumulative concrete strategies are identified by procedures used earlier by J. P. Denny (personal communication), from whom the idea of this kind of analysis was borrowed.

Table 1

Observed and Predicted Proportions of Correct Choices as a Function of Trial Number and Congruence Value (i)

Group	(i Value)	Trial 1	2	3	4
1	Observed	.680	.480	.800	.840
	Predicted - Local Consistency Model	.581	.326	.551	.700
	Predicted - Passive States Model	.585	.362	.527	.677
2	Observed	.640	.840	.760	.760
	Predicted - Local Consistency Model	.581	.663	.719	.766
	Predicted - Passive States Model	.585	.642	.711	.760

Table 2

Comparison of Observed and Predicted Relative Frequencies of All Possible Sequences of Responses in Each Group

(Predictions Based on Minimum Squared Error Fits for Two Local Consistency Models.)

	$i = 1$			$i = 2$		
Sequence	Observed	Restle Model	Passive State Model	Observed	Restle Model	Passive State Model
RRRR	.120	.186	.182	.280	.236	.230
RRRW	.040	.000	.002	.120	.049	.048
RRWR	.080	.000	.010	.080	.066	.065
RRWW	.000	.000	.019	.040	.033	.033
RWRR	.280	.131	.123	.080	.099	.103
RWRW	.080	.000	.002	.000	.033	.035
RWWR	.080	.088	.082	.040	.044	.047
RWWW	.000	.175	.164	.000	.022	.024
WRRR	.240	.140	.127	.160	.175	.161
WRRW	.000	.000	.002	.080	.035	.035
WRWR	.000	.000	.007	.080	.047	.047
WRWW	.000	.000	.014	.000	.023	.023
WWRR	.040	.093	.088	.040	.070	.074
WWRW	.000	.000	.002	.000	.023	.025
WWWR	.000	.062	.059	.000	.031	.034
WWWW	.040	.124	.118	.000	.016	.017

Table 3

Proportions of Persons Judging a Dimension to be Relevant after Each Trial

(Parenthesized entries are for correct hypotheses only.)

Dimension	Group 1 After Trial 1	Group 1 After Trial 2	Group 1 After Trial 3	Group 2 After Trial 1	Group 2 After Trial 2	Group 2 After Trial 3
AYE-BEE	.36	.44	.40	.32	.52	.32
UP-SIDEWAYS	.36(.24)	.72(.68)	.84(.76)	.36(.36)	.60(.56)	.84(.72)
CAPITAL - LOWER CASE	.40	.84	.24	.28	.36	.28
Average for irrelevant dimensions	.38	.64	.32	.30	.44	.30

Table 4

Proportion of Hypothesis Judgments Consistent with Different Strategies for Making Those Judgments

Strategy	Group 1 (i = 1) After			Group 2 (i = 2) After		
	Trial 1	Trial 2	Trial 3	Trial 1	Trial 2	Trial 3
Cumulative Deductive	.600	.467(b)	.573(c)	.600	.227	.627(e)
Current Feedback	.200(a)	.333	.427	.293(d)	.400	.427
Cumulative Concrete	.200(a)	.467(b)	.573(c)	.293(d)	.413	.613(e)
At least one of the above	.800	.600	.747	.893	.627	.787

Note: The two proportions marked (a) are forced by definition to be equal. A similar statement holds for (b), for (c), and for (d). In the case of (e) it is logically possible for the two entries to differ by as much as .027.

Table 5

Frequencies of Different Categories of Errors in Hypothesis Judgments for Present Experiment's Groups and for Berger's Experiment

Category	Nature of Processing Error	Total Number of Errors Per Group: Present Experiment i = 1	Present Experiment i = 2	Berger's Experiment
1	First H opposite to first feedback	8	2	112
2	NR after first feedback	7	5	141
3	Reversal of an H without reversal of feedback	4	2	104
4	Premature exclusion of a dimension, including rejection of correct H	2	13	285
5	Failure to respond NR when implied	44	22	320
6	Reversal of H, consistent with current feedback, ignoring the fact that reversed feedback implies NR	6	9	180
7	From NR, select H consistent with current feedback	6	3	185
8	From NR, select H inconsistent with current feedback	0	2	66
9	NEI to NEI when correct H is implied	4	0	Not Possible
10	Failure to retain correct H	1	2	Not Possible
11	NR to NEI	3	5	Not Possible
	Total	85	65	

Table 6

Consistency of Choice Behavior with Hypotheses Reported Immediately Before

	Group 1 After FT			Group 2 After FT		
	1	2	3	1	2	3
Consistent with 1 H	2	8	13	7	7	10
both of 2 Hs	0	1	2	1	1	3
all 3 Hs	0	0	0	1	0	0
Contradictory to 1 H	6	7	0	3	0	3
both of 2 Hs	2	0	3	1	5	0
all 3 Hs	0	0	0	0	0	0
Proportion consistent trials	.200	.567	.833	.692	.615	.812
Combined groups' pro-proportion consistency	.478	.586	.824			