Behavioral Problems of Adhering to a Decision Policy

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> "While you are following any set of rules and policies, follow them to the letter. It is the only way they can help you."
>
> - Edwards & Magee, 1966

The need for an investment policy, carefully thought out and personalized to accommodate the investor's particular objectives, is widely acknowledged. Once a policy is decided, the investor is advised to stick to it steadfastly as exemplified by the quote by McGee and Edwards at the beginning of the handout. Many investors have attributed their failures to their inability to adhere to predetermined plans.

In my talk today, I am going to analyze the problems of adhering to policy from a psychological viewpoint. Some research will be described which indicates that we do indeed deviate from the policies we wish to follow. There are two key elements behind such deviations. The first stems from changes over time in the goals, aspiration levels, or criteria that underlie our policies. Often, these changes are triggered by the fact that we are earning money or losing money. The second facet of nonadherence involves certain deficiencies in our thought processes.

These deficiencies allow two villains—random error and systematic bias—to obliterate our policies, often without our awareness of the fact that this is happening.

After reviewing research that demonstrates the ways in which we fail to adhere to policy, I'll close with a discussion of some techniques aimed at helping decision makers to follow their policies.

Let's look first at changes over time in our goals or decision criteria. At an intuitive level, almost everyone agrees that it's hard to follow a predetermined policy when your financial condition is riding the crest of good fortune or plummeting with a bear market.

For example, Gerald Loeb notes that a bull market causes us to: congratulate ourselves for being such astute investors and to think how foolish we were to have been so conservative or how much better off we would be if we had taken greater risks. He cautions the investor to “stick to your long-term investment plan, not modified by the fears or exuberance of the moment.”

Surprisingly, there is very little research on the stability of a person’s risk-taking behavior in the face of emotional turmoil caused by gaining or losing money; but what research there is supports our intuitive perceptions to the effect that changes in our state of wealth do change our risk-taking policies.

Some of the most interesting research on this problem was done by McGlothlin in 1956. He studied the effects of prior wins and losses upon subsequent betting at the race track. McGlothlin found that, when it came time for the last race of the day, bettors tended to underbet the favorite and overbet long-shot horses. McGlothlin attributed this overbetting of long shots to the bettors' desire to recoup their losses with a big winning payoff. Since the favorites were going off at larger odds than they should have, those who did bet on them in the last race actually had a slight positive expected value going for them.

Race tracks typically return about 83¢ for every dollar invested by the bettors. So, as the racing day proceeds, and the bettors as a group fall farther behind, it is interesting to note that the proportion of horses bet to win increases while the proportion of place and show bets decreases. Win bets offer lower probabilities of winning, but higher payoffs. So this result is also consistent with the idea that willingness to take risks increases after a financial loss. Finally, McGlothlin showed that the amount of money wagered on a race was positively correlated with the odds of the winning horse in the previous race. Thus, after a race won by a long shot (which means that most bettors lost), more money was wagered than if the favorite had won. Again, this indicates that losing bettors increase their risk-taking propensities in an attempt to recoup their losses.

Sarah Lichtenstein and I have recently conducted a study in Las Vegas where we confirmed McGlothlin's findings of greater preferences for high risk, high payoff gambles by gamblers who were losing money. We also found that gamblers who were ahead of the game became more conservative, placing greater emphasis on getting bets with high probabilities of winning, and thus preserving their newly-acquired wealth. There seems to be other circumstances in which just the opposite occurs. That is, where good fortune induces people to take greater risks than they ordinarily would accept.

It is not necessarily inappropriate to change one’s financial objectives or risk-taking propensity as a result of a change in financial position. If the change is a substantial one that is likely to be relatively permanent, the investor's goals should be revised. Less defensible, of course, is a change of policy after a small, or temporary, change in wealth.

One other type of situationally-induced change should be mentioned here. There have been many recent studies in which the level of risk acceptable to a group has been compared to the risk acceptable to the individuals who comprise the group. In situations where society as a whole values a conservative approach, groups make more conservative decisions than the average of their individual members. Where society values risk, the reverse holds true—that is, groups are riskier than individuals. Thus, we see that individuals change their policies towards risk-taking when they enter the group setting.

Next I'd like to focus on some aspects of policy implementation that are more subtle in nature and less familiar to us in an intuitive sense. These have to do with the notion that the faithful execution of one's own decision policies involves a considerable degree of skilled thinking.

It is commonly believed that we can infer an individual's policy by looking closely at his actual judgments and decisions. However, recent research indicates that this may not always be true. Instead, there is now evidence which indicates that a person's judgments and decisions may often reflect his true policies imperfectly, due to the action or random error and systematic biases. Faithful adherence to policy appears to require a degree of skilled thinking that often exceeds the capabilities of human intuition.

Let's look first at random error. The quote by Goldberg on page two of your handout describes the problem of error and unreliability rather eloquently. He says:

> He [the judge] "has his days": Boredom, fatigue, illness, situational and interpersonal distractions all plague him, with the result that his repeated judgments of the exact same stimulus configuration are not identical. He is subject to all those human frailties which lower the reliability of his judgments below unity. And, if the judge's reliability is less than unity, there must be error in his judgements—error which can serve no other purpose than to attenuate his accuracy. If we could remove some of this human

unreliability by eliminating the random error in his judgments, we should thereby increase the validity of the resulting predictions. (Goldberg, 1970)

The presence of random error in highly-skilled judgment was demonstrated by Garland, who studied the reliability of radiologists as they attempted to detect the presence of lung disease on X-ray films. Garland found that a radiologist changed his mind about 20% of the time when reading the same film on two occasions.

Another example of inconsistency comes from a study of expert horse-race handicappers, which we are currently conducting at the Oregon Research Institute. We're not really interested in horse-race predictions, we're studying the stresses caused by information overload, and horse racing provides an appropriate context in which to do this. We expect that the results will generalize to any domain in which the skilled integration of large masses of quantitative information is performed by means of human judgment. For horse-race handicapping is an information game, much as investment analysis is an information game, and although there are many differences between these two domains of risk-taking, there are many similarities as well. Figure 1 shows a typical past-performance chart, which gives detailed information about each horse's recent performances. It doesn't take too much imagination to see the similarities between these kinds of charts and the data sources used in some forms of financial analysis.

Our judges in this study were eight individuals, carefully selected for their expertise as handicappers. Each judge was presented with a list of 88 variables culled from the past-performance charts. He was asked to indicate which five variables out of the 88 he would wish to use when handicapping a race, if all he could have was five variables. He was then asked to indicate which 10, which 20, and which 40 he would use if 10, 20, or 40 were available to him. Table 2 illustrates the five variables chosen by one of the handicappers. The upper part of the table lists the variables by name. The lower part provides the values of each variable for the eight horses in one of the 40 races the handicapper was to judge. Table 3 shows the list of 40 variables chosen by this same handicapper.

Each handicapper judged each of 40 races under all four information conditions. First he would see five variables and then rank the top five horses in the order he thought they would finish. He then received his first 10 variables and researched the horses. He then ranked them again using 20, and finally 40, variables.

We had all of the information stored in a computer so the computer could print out the appropriate variables for every race. Each handicapper had his own personalized set of five, 10, 20, and 40 variables.

Five of the 40 races were repeated at the end of the experiment. By examining the two rankings for the same race, we can assess the degree of random error in the prediction policies of our handicappers.

Before examining inconsistency, though. let's look at how accuracy and confidence varied with amount of information as shown in Figure 4 of the handout. We see that accuracy was as good with five variables as it was with 10, 20, or 40. The flat curve is an average over eight subjects and is somewhat misleading. Three of the eight actually showed a decrease in accuracy with more information, two improved, and three stayed about the same. All of the handicappers became more confident in their judgments as information increased.

In Table 1, we see a comparison of the amount of inconsistency in our handicappers' judgments at low and high levels of information. Consistency was measured in three ways—by the number of times the first-place horse was changed when the race was judged the second time, by the number of changes in any of the five ranks, and by the sum of the differences in ranks from one time to the next. Each of these measures told the same story—there was considerable inconsistency in the rankings, and this inconsistency increased as the amount of available information increased.

These results should give some pause to those of us who believe we're better off by getting as many items of information as possible, prior to making a decision.

Next, I'd like to describe some research using a technique called the "lens model," which further indicates the disruption of decision policies by inconsistency.

Before describing the model, let me describe the subject's task which is called a "multiple-cue probability learning task." This awful-sounding task was developed to embody certain fundamental aspects of important real-world judgment situations. First, there are several cues that the judge must learn to us, in order to predict some criterion value. These cues differ in importance, and they can differ in the form of their functional relationship to the criterion.

A specific example, shown on page two of the handout, may help clarify things. There are three cues $\begin{Bmatrix} A & B & C \\ X_1 & X_2 & X_3 \end{Bmatrix}$ with numerical values between one and 10. The criterion, Y_e, is a number between one and 20.

The subject is shown the cue values of A, B, C. He makes a judgment, and then is shown the correct answer. (See display in the handout). In the experiments I'm going to describe, this is repeated for 200 learning trials. The subject is supposed to learn how to predict the correct answer from knowledge of the three cues.

The experimenter controls the learning environment by means of a "policy equation," which indicates how the criterion is related to the cues. Shown in the handout are two equations—one linear, the other nonlinear—which were used in the studies to be described. In the nonlinear case, each cue is related to the criterion by an upside-down U-shaped function, as indicated in the handout. Notice the term E in the linear and nonlinear equations. This represents the small amount of error which was added to the environment to simulate the natural uncertainty in the world.

Now, keeping the linear task in mind, let's turn to the rather gruesome looking Figure 5 in the handout. Figure 5 shows what is called the Lens Model for reasons that, if not obvious, aren't worth mentioning. It describes the statistics used to evaluate a judge's performance in a multiple-cue learning tasks like those we've been talking about. One slight discrepancy is that in the Figure the cue dimensions A, B, and C are called X_1, X_2, X_3, etc.

The cue values, X_1, X_2, etc., change from trial to trial. On each trial, the subject makes a response Y_s. Over a block of trials, this response can be correlated with the correct answer or criterion, Y_e. The index of subject's achievement, denoted by the symbol r_a, is simply the correlation between Y_e and Y_s.

If the policy equation controlling the environment is linear, like Equation 1 at the lower left of Figure 5, we can use it to predict the environment. We can build a similar equation to predict the subject, as in Equation 2 in Figure 5. The correlation between the two predicted scores $\hat{Y}_e$ and $\hat{Y}_s$, is called G, the matching index. G will be high if the subject is employing the correct policy equation—that is, appropriate weights and functions. The degree to which the equation of the subject can actually predict the subject's own responses is indicated by the correlation between Y_s and $\hat{Y}_s$, designated R_s. R_s is an index of the amount of error in the subject's execution of his own policy equation. Ken Hammond, who is responsible for all this, calls R_s an index of the subject's cognitive control.

These relationships are listed at the top of page 3. Also listed there, on line 5, is the lens model equation showing that subject achievement, r_a, can be expressed as a product of G, R_s, and R_e.

Figure 6 shows the performance of subjects who were trying to learn the linear and nonlinear policies described on page two. The values of r_a, R_s, and G are computed for each of 10 blocks, with 20 trials in each block. We can see that learning of the linear task is fast, but learning is relatively poor in the nonlinear task. Before discussing this further, let me note that we can compute the matching index, G_1, even in the nonlinear case, by using the appropriate nonlinear equations to predict the criterion and the subject's responses. Looking at the right-hand side of Figure 6, we see that G was quite high by the end of the 200 learning trials. This means that subjects learned what the appropriate nonlinear function was. The reason their achievement, r_a, was so low was because of a low degree of consistency (R_s, the thin solid line). We see that subjects learned the correct policy, but could not employ it as consistently as they should have.

Figure 7 shows the results of another study using this same nonlinear task. Subjects in two of the three groups were told the correct policy equation after 20 trials. As the center graph shows, G quickly jumped almost to 1.00 and stayed high for these two groups. If you look at the right-hand graphs, you'll see that R_s, the index of consistency or control, was also high, provided that subjects did not get correct-answer feedback. If they did receive correct-answer, or outcome, feedback, their control over the execution of their policies was disrupted and their performance suffered. There was a slight bit of error added into the task equation so that the criterion, Y_e, was not perfectly predictable. The outcome feedback thus contained some random error, and this apparently induced the subjects to be inconsistent in applying their own policies.

These studies indicate how random error can disrupt judges' policies. Let's look briefly at another disruptive element—systematic bias. At Oregon Research Institute, we have spent several years studying the ways that a person's limited memory, attention, and reasoning capabilities induce systematic biases that result in his decisions being inconsistent with his "true preferences or beliefs" (true policies).

The failure of one's decisions to appropriately reflect his personal values or policies can be considered one of the most fundamental aspects of nonoptimal decision making. One example of this comes from an experiment that Sarah Lichtenstein and I did in 1968. In this study, we asked individuals to indicate how much they would like to play various gambles. The attributes of the gambles, which had to be integrated into the overall judgment, were the gambles' probabilities of winning and losing and the winning and losing payoffs. The experiment was straightforward. One group of subjects rated the attractiveness of playing each gamble on a 10-point scale. A second group of subjects indicated the attractiveness of these same gambles by a bidding method in which they put a price tag on each to indicate its worth to them. That is, they stated an amount of money such that they would be indifferent between playing the gamble and receiving the stated amount. In addition, some of the subjects in these groups indicated their subjective beliefs about the relative importance of the four attributes of a gamble (i.e., probability of winning, probability of losing, amount to win, and amount to lose). When subjects rated the attractiveness of a gamble, probability of winning was found to be the most important dimension. When they put a price on a gamble, attractiveness was determined primarily by the gamble's payoffs. Yet subjects in both groups stated that they valued probability of winning as the most important attribute. Apparently, there was a failure to give proper consideration to this value when making the pricing responses.

Another experiment, conducted on the floor of the Four Queens Casino in Las Vegas, demonstrated a similar response-mode effect. Consider the following pair of gambles used in the Las Vegas experiment:

Bet A	Bet B
11/12 chance to win 12 chips	2/12 chance to win 79 chips
1/12 chance to win 24 chips	10/12 chance to lose 5 chips

where the value of each chip has been previously fixed at, say, 25¢.

Notice that Bet A has a much better chance of winning but Bet B offers a higher winning payoff. Subjects were shown many such pairs of bets. They were asked to indicate, in two ways, how much they would like to play each bet in a pair. First they made a simple choice, A or B. Later they were asked to assume they owned a ticket to play each bet, and they were to state the lowest price for which they would sell this ticket.

Presumably these selling prices and choices are both governed by the same underlying quality, the subjective attractiveness of each gamble. Therefore, the subject should state a higher selling price for the gamble that he prefers in the choice situation. However, the results indicated that subjects often chose one gamble, yet stated a higher selling price for the other gamble. For the particular pair of gambles shown in the handout, Bets A and B were chosen about equally often. However, Bet B received a higher selling price about 88% of the time. Of the subjects who chose Bet A, 87% gave a higher selling price to Bet B, thus exhibiting an inconsistent preference pattern.

What accounts for the inconsistent pattern of preferences among almost half the subjects? We have traced it to the fact that subjects use different weighting policies for setting prices than for making choices. Subjects choose Bet A because of its good odds, but they set a higher price for B because of its large winning payoff. Because the responses are inconsistent, it is obvious that at least one kind of response does not accurately reflect what the decision maker believes to be the most important attribute in a gamble.

We can measure a person's utility for risk in terms of his preference for low probability-high payoff bets. We obtained two measures of preference for long-shot bets for each of our subjects—one measure was based on the subject's choices among bet pairs like the one in the handout. The other was based on his selling prices for these same bets. The correlation across subjects, between these two measures of the same characteristics, was only .46. A scatterplot of this relationship is shown in Figure 8 of the handout. Each dot in the figure is a person. Perfect consistency would cause these dots to fall on a straight line. Again, we see how this slight change in response—from choice to pricing—disrupts people's risk-taking policies.

Another kind of systematic bias was demonstrated in a recent experiment in which we predicted that dimensions common to each alternative in a choice situation would have greater influence upon decisions than would dimensions that were unique to a particular alternative. We asked subjects to compare pairs of students and predict which would get the higher college Grade Point Average. The subjects were given each student's scores on two cue dimensions (tests) on which to base their judgments. One dimension was common to both students and the other was unique. Some examples of the format we used are shown in Table 3 on page 10 of the handout. For example, Student A might be described in terms of his scores on Need for Achievement and Quantitative Ability, while Student B might be described by his scores on Need for Achievement and English Skill. In this example, since Need for Achievement is a dimension common to both students, we expected it to be weighted heavily. We figured that a comparison between two students along the same dimension should be easier, cognitively, than a comparison between different dimensions, and this ease of use should lead to greater reliance on the common dimension. The data strongly confirmed this hypothesis. Dimensions were weighted more heavily when common than when they were unique attributes. Interrogation of the subjects after the experiment indicated that most did not wish to change their policies by giving more weight to common dimensions and they were unaware that they had done so.

The message in these experiments is that the amalgamation of different types of information and different types of values into an overall judgment is a difficult cognitive process. In our attempts to ease the strain of processing information, we often resort to judgmental strategies that do an injustice to the underlying values and policies that we're trying implement.

Investment policies are often based on some expected level of performance—expected rate of return, expected risk, expected covariation, etc. If we feel that the returns on our investments are not running true to form we may be tempted to assume that we made a mistake in our calculations or that there has been a fundamental change in the conditions underlying those calculations. Either assumption could be considered grounds for rearranging our investments in an attempt to get them to conform to the properties we desire.

The problem is that the probabilistic nature of investment parameters leads them to fluctuate randomly about their expected performance levels. It takes a statistician to determine whether observed deviations are due to factors other than random chance. If we attempt to make such judgments intuitively, we're likely to fall victim to another systematic bias—the underestimation of sampling variability. Psychologists Tversky and Kahneman have found that even people with statistical training overestimate the validity of small samples of data when they are relying solely on their intuition. People are too quick to interpret a deviation from expected values as due to a change in the world, rather than mere sampling variability. Tversky and

Kahneman concluded that the only effective precaution against overreacting to small samples of data is to employ formal statistical procedures, rather than intuition, to evaluate deviations from expected levels of performance.

A major problem that a decision maker faces in his attempt to be faithful to his policy is the fact that his insight into his own behavior may be inaccurate. He may not be aware of the fact that he is employing a different policy than he thinks he's using. This problem is illustrated by a study that Dan Fleissner, Scott Bauman, and I did, in which 13 stockbrokers and five graduate students served as subjects. Each subject evaluated the potential capital appreciation of 64 securities. Figure 9 illustrates the way that information about each company was displayed. A mathematical model was then constructed to predict each subject's judgments. One output from the model was an index of the relative importance of each of the eight information items in determining each subject's judgments. These importance weights are shown at the top of Table 4. Below them in Table 4 are the subject's perceptions of their weighting policies. Examination of Table 4 shows that the broker's perceived weights did not relate closely to the weights derived from their actual judgments. For example, Broker 6 thought he gave most weight to Industry, but he actually gave that factor less weight than any other. The importance of Industry was consistently overestimated by the brokers; also, Volume was perceived as more important than resistance and support, a fact that was not evident in the policies calculated from the actual judgments. The students' perceptions were more accurate than the brokers. This prompted an examination of the relationship between number of years' experience as a broker and accuracy of self-insight. The correlation was -.43, indicating a tendency for the more experienced brokers to be less accurate in perceiving their own weighting policies.

Well, if I've been successful in demonstrating the variety of problems involved in adhering to a decision policy, the natural question at this point is—what can be done to facilitate adherence to policy?

There are at least three basic therapies we can try. The first is a tonic to reduce random error, called bootstrapping. It is applicable in situations where a judge or decision maker makes a large number of decisions on the basis of quantitative information. Bootstrapping involves building a model to represent the judge's decision policy. This model may take the form of an algebraic equation or it may be a complex decision tree like Clarkson's model of a bank's trust investment officer. Once the model is available, it can be substituted for the decision maker. The advantage is that the model can be applied without error. Surprisingly, this actually works. There are a number of studies in which a judge's model is shown to outperform the judge himself in predicting some criterion.

Of course, the bootstrapping procedure preserves any systematic biases in the judge's behavior. Implicit in the use of bootstrapping is the assumption that these systematic biases will be less detrimental to performance than the inconsistency of unaided human judgment.

The second technique for facilitating adherence to policy is based on the decomposition principle. Rather than trying to infer policy from the decision maker's behavior, we can ask him directly about all the essential elements of his policy. We can ask him to indicate the relevant attributes and their weights and we can then combine these by means of some logically optimal model. The difference between this and bootstrapping is that in bootstrapping we attempt to infer the policy by observing a representative set of decisions. With decomposition, we ask the decision maker directly about his policy and then build a model to apply that policy with consistency. We are presently doing an experiment at Oregon Research Institute that attempts to determine whether the decomposition approach can improve upon an expert's intuitive judgments.

The third approach to helping a decision maker abide by his policies comes out of the "lens model" research discussed earlier. Remember the task with the three cues A, B and C, each related to the criterion by an inverse U-shaped function, and each having a different importance weight? Recall that performance on this task is impaired by subjects' inability to apply their policies with consistency. Hammond has shown that consistency in this task, and thus achievement, improves dramatically when subjects are given computerized feedback, as shown in Figure 10 of your handout. The subjects make a series of 10 judgments. The computer then displays the key elements of their policies (their weights and the functional relationships between the cues and their responses). It also shows them the optimal or desired policy so they can compare the components of their policies with the policy they should be employing. Figure 11 compares the performance of a subject who received this computer feedback with the performance of subjects who received more traditional kinds of feedback. Performance is quite good for the computer graphics group and Figure 12 indicates why both G and R_s are high. This type of feedback helps individuals apply the correct policy with relatively little random error.

Although my knowledge of investment policies is limited, it seems to me that this kind of computerized feedback could be employed just as readily to help an investor compare his actual policy with the ideal policy he was striving to achieve.

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BEHAVIORAL PROBLEMS OF ADHERING TO A DECISION POLICY

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". . . while you are following any set of rules and policies, follow them to the letter. It is the only way they can help you [Edwards & Magee, 1966]."

I. Introduction

A. Statement of the problem

B. Overview of this presentation

1. key facets of nonadherence to policy

a. changes in criteria, goals, or aspiration levels
b. lack of necessary cognitive skills: random error and systematic bias

2. techniques to facilitate adherence to policy

II. Changes in Criteria, Goals, or Aspirations

A. Wall Street folklore and research agree: sudden gains and losses can alter one's goals and, accordingly, one's propensity for taking risks.

1. McGlothlin (1956) found that losing bettors at the race track developed increased preferences for low probability, high payoff bets in an attempt to recoup their losses. Research in Las Vegas shows that gamblers who win money sometimes become more conservative.

2. Changes in policy are desirable if they are in response to relatively stable changes in financial position.

B. Group decisions embody risk-taking criteria different than the criteria of the individuals in the group.

III. Policy Implementation as Skilled Thinking

A. Contrary to popular belief, an individual's overt judgments and decisions may reflect his "true decision policies" only imperfectly; observed judgments deviate from desired policy due to the presence of random error (inconsistency) and systematic biases. Faithful adherence to policy requires a degree of cognitive skill that may often exceed our intuitive capabilities.

B. Random error

1. "He [the judge] 'has his days': Bordeom, fatigue, illness, situational and interpersonal distractions all plague him, with the result that his repeated judgments of the exact same stimulus configuration are not identical. He is subject to all those human frailties which lower the reliability of his judgments below unity. And, if the judge's reliability is less than unity, there must be error in his judgments--error which can serve no other purpose than to attenuate his accuracy. If we could remove some of this human unreliability by eliminating the random error in his judgments, we should thereby increase the validity of the resulting predictions [Goldberg, 1970]."

2. Studies by Garland (1959) and others have revealed a surprising degree of inconsistency when a physician diagnoses the same case on two or more occasions.

3. A study of expert horse-race handicappers shows that as the amount of available information increases (a) accuracy remains stable, (b) confidence rises sharply, and (c) judgment policies exhibit more random error.

See Figures 1, 2, 3, & 4, and Table 1

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4. Research with the "lens model" illustrates the importance of "cognitive control."

   a. the learning task (multiple-cue probability learning)

3   3 cues $\left\{\begin{matrix} X_1, X_2, \& X_3 \\ A, B, \& C \end{matrix}\right\}$ with numerical levels between 1 and 10

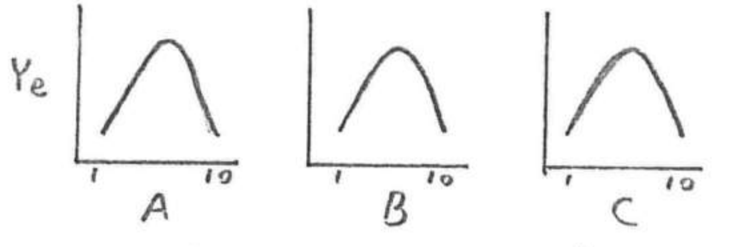
a criterion (Y_e) that ranges between 1 and 20

policy weights: A = .4, B = .8, C = .2

task equations (policies to be learned):

linear $\quad Y_e = .4A + .8B + .2C + \text{Error}$

nonlinear $\quad Y_e = .4(\alpha_1 A^2 + \alpha_2 A + \alpha_3) + .8(\alpha_1 B^2 + \alpha_2 B + \alpha_3) + .2(\alpha_1 C^2 + \alpha_2 C + \alpha_3) + \text{Error}$



Function Forms in Nonlinear Task

Trial 001		
A	B	C
5	8	4
	Your J	___
	Correct J	___

A, B, C change from trial to trial for 200 trials.

basic stimulus display

Petife Drake 110 Lt. ch. f, 3, by Admiral Drake—Petite Soeur, by Beau Pere.
Breeder, G. G. Jamieson. 1960 3 M 0 0 ——
Owner, Mr. & Mrs. G. G. Jamieson. Trainer, L. W. Kidd. $5,000 1959 0 M 0 0 ——
May11-601B.M 6 f 1:12⅖ft 56 113 1½ 2h 22 54¾ ScheihF3 M5000 76 VegasBoy118 Gasperlee118 PioneerJoe 12
Apr27-601B.M 6 f 1:13⅖sy 73 108* 4¾ 59 7151017 D'l'gE12 M6500 59 L'leSpinet114 Tr'scribe118 T'xasT'b'ine 12
Mar15-601B.M 6 f 1:13 ft 48 113 84¾ 91011151119 Sch'hF12 M5000 59 TheWave114 Nightken113 Web'sReg'rds 12
May 6 BM 3-8 ft :36⅔h May 2 BM 3-8 ft :35⅕h April 26 BM 5-8 ft 1:03⅗b

Royal Jane 115 Ch. f, 3, by Texas Sandiman—Fighting Jane, by Silver Horde.
Breeder, O. J. Todd. 1960 4 M 0 0 $125
Owner, Mr. & Mrs. E. H. Sorrell. Trainer, J. Weatherington. $5,000 1959 0 M 0 0 ——
May 4-605B.M 6 f 1:12⅘ft 40 113 43½ 52¼ 55 58½ Harm'zW8 5000 70 Starl'tTow'r108 Q'tWaters112 Wahalis 8
Apr26-601B.M 6 f 1:11⅕ft 9¼ 115 52¼ 73¼ 78½ 711 PierceD3 Mdn 76 MissJoyce110 Himalaya115 Heione 12
Mar31-605B.M 6 f 1:12 ft 173 113 14 12 1h 43½ PierceD2 4000 79 Q'tWaters112 Facetieux113 BernO'Dine 12
Mar25-601B.M 6 f 1:11⅘ft 53 108 104¾ 87¼ 811 812 ShirotaM5 3500 72 HighDrag112 EdwardJ.114 RareToubo 12
April 20 BM 5-8 ft 1:01⅘h April 10 BM 3-8 ft :36⅕h March 23 BM 1-2 ft :49h

Bold Dust 115 B. f, 3, Bold Gallant—Garara, by Nirgal.
Breeder, E. J. Harris. 1960 3 M 0 0 ——
Owner, E. & J. Harris. Trainer, F. Jolosky. $5,000 1959 2 M 0 0 $40
May 4-602B.M 6 f 1:12⅗ft 251 114 5¾ 101410141014 HuntG1 Mdn 66 Minnigerode118 HearYe118 Zipper-Bee 12
Apr28-601B.M 6 f 1:14 sl 182 115 21¼ 45 59 612 HuntG10 Mdn 61 Sals-R'ge115 Sm'IT'wnGirl115 Kylew'd 12
Apr14-601B.M 6 f 1:11⅘ft 99 114 85¼101010111019 HuntG7 Mdn 65 GoHost118 Principillo118 FoxyRudy 11
Sep23-595Pom a 6 f 1:14⅕ft 24 116 86½ 89 79 616 Cant'iJ4 M5000 66 Dimity115 MissGenelle116 SunC. 8
Sep 3-591Dmr 6 f 1:11⅗ft 88 116 101211191118118 G'ithsR9 M7500 68 Gladiola116 PaulineK.111 SocietyRose 12
May 9 BM 3-8 ft :36⅕h April 4 BM 5-8 ft 1:05b

Adagio 115 Ch. f, 3, by Esprit de France—Nautch Girl, by Soodani.
Breeder, Parkhill Larms Ltd. 1960 11 M 0 3 $485
Owner, Mr. & Mrs. N. C. Archer. Trainer, N. C. Archer. $5,000 1959 7 M 1 1 $302
May10-604B.M 6 f 1:12 ft 32 115 87 88¾ 55 34¾ HuntG6 M5000 76 Facetieux110 FlowerDeck115 Adagio 12
Apr 2-601B.M 6 f 1:10⅘ft 122 113 117¾118¾10141015 GlennP9 4500 74 Stencil116 ArmedMiss116 DarkSh'dows 11
Mar17-601B.M 1 1/16 1:45⅕ft 50 113 87¾101710241027 Gl'nnP10 M5000 51 Unrestr'ned113 K'rnPr'ss113 Brok'nL've 11
Mar10-601B.M 6 f 1:12⅕ft 25 113 115¾105¾ 510 67¼ GlennP4 M5000 75 Pr'ssG'ki114 Chic'oMiss108 Unrestr'ned 12
Mar 5-601B.M 6 f 1:12 ft 27 107 84½ 57½ 613 69¾ GlennP5 3500 73 Reg'lGl'a109 Capt'nBos'n113 Q'tWaters 9
Feb22-603TuP 5½ f 1:06 ft 8½ 115 52¾ 64 52¾ 54¼ Dittf'chH4 Mdn 80 TribalSec't120 Fr'tyBomb115 Unwritt'n 12
Feb17-603TuP 6 f 1:12⅖ft 5½ 113 55 55½ 76¼ 87 FreyP10 M3500 76 JakeH'grass120 Ete'lLiz115 Time'sLast 12
Jan20-603TuP 6 f 1:13 ft 3½ 110*1113 811 35 23 Mu'yK12 M2500 77 PanchoDee120 Quico120 NowOn 12
Jan17-601TuP 5½ f 1:08⅗gd 3¾ 115 73¼ 54 4¾ 44¼ Dittf'chH3 Mdn 68 WingLo115 Transcribe115 BullCamp 10
Jan 8-601TuP 6½ f 1:19⅖ft 25 110* 73¼ 73¼ 3½ 3½ MurrayK3 Mdn 76 Jean'sChes't120 Directly120 Transcribe 10
May 6 BM 5-8 ft 1:02⅖hg April 25 BM 3-4 ft 1:16⅗h April 21 BM 3-8 ft :36⅗h

Painted Pet 115 Ch. f, 3, by Mafosta—Gold Paint, by Gold Bridge.
Breeder, F. R. Graham. 1960 2 M 0 0 ——
Owner, Montrose Stable. Trainer, K. R. Darbyshire. $5,000 1959 8 M 0 1 $130
May10-604B.M 6 f 1:12 ft 7¾ 115 21 32 43½ 610 Art'rnJ5 M5000 73 Facetieux110 FlowerDeck115 Adagio 12
Apr21-601B.M 6 f 1:13⅗ft 30 113 916102110291024 V'zkeM3 M5000 51 D'm'dMark118 Kitsimbanyi113 P'n'rJoe 12
Dec14-593B.M 6 f 1:13⅘ft 17 116 54 74½ 95¾ 85½ YakaR7 M5000 68 TurkishNight116 SunnyNote116 SunC. 12
Dec10-591B.M 6 f 1:13⅕ft 22 114 83½ 94 11261127 YakaR11 M5000 50 Slippery117 NoExit114 MarketSpecial 12
Jun29-592L.P 4½ f :53⅘ft 10 117 7 44 32½ 33 Rich'dson5 Mdn MyBoyJ'n113 FoxeeLucee110 TigerTh'y 10
Jun25-592L.P 4½ f :54⅕ft 5¼ 117 8 77¼ 87½ 77 Cop'nollK2 Mdn BraveKni't113 FoxeeLucee110 Y'gRuf'n 10
Jun15-592L.P 4½ f :53⅕gd 5¼ 118 6 44 45 46¼ Cop'nollK4 Mdn Ur-Mia118 AmcanCathy111 Kydette 9
May 8-593Tan 5 f 1:01⅕ft 15 117 73¼ 85¼ 89¾ 79¼ V'zkeM9 M6000 78 BlueTish117 Nina deTejas117 Step gBy 11
May 4-593Tan 5 f 1:00⅖ft 24 117 64¼ 53½ 43 78¾ Art'burnJ7 Mdn 82 Svalan117 Lady d'Arg't112 N'a deTejas 7
Apr20-593Tan 5 f 1:01 ft 8¾ 115 1½ 2h 43½ 79¼ V'zkeM2 M8000 79 MissJ'hnnieD.115 T'mO'Farrell118 Reins 11
May 9 BM 3-8 ft :35⅗h May 5 BM 1-2 ft :48⅗hg April 13 BM 5-8 ft 1:05bg

Continuity 115 Ch. f, 3, by Balsamo—Sunny Pharlara, by Sun Briar.
Breeder, O. R. Harrod. 1960 5 M 0 1 $375
Owner, Mr. & Mrs. N. Jensen. Trainer, N. Jensen. $5,000 1959 3 M 0 0 $25
May10-601B.M 6 f 1:11⅗ft 28 115 74¼ 56½ 37 34¾ Art'rnJ6 M5000 80 Pilikia115 TilliesBaby110 Continuity 12
May 4-604B.M 1 1/16 1:45⅗ft 175 113 11 78¼ 717 816 Art'burnJ5 Mdn 60 Peno118 Principillo118 EdenBelle 8
Apr28-601B.M 6 f 1:14 sl 18 115 96¾ 78¼ 611 512 Ar'burnJ11 Mdn 61 Sals-R'ge115 Sm'IT'wnGirl115 Kylew'd 12
Apr21-601B.M 6 f 1:13⅗ft 52 113 55¾ 54¾ 46½ 48¼ Art'rnJ7 M5000 67 D'm'dMark118 Kitsimbanyi113 P'n'rJoe 12
Mar29-604B.M 6 f 1:12 ft 110 113 85¾ 78¼ 79½ 711 Art'burnJ8 Mdn 72 KerryPiper118 Graphite118 Nightken 12
Sep 3-591Lga 5½ f 1:08⅗gd 59 115 108¼106¾106½ 55¾ FreyP4 M5000 70 Warbr'k118 Mirac'l'm118 Dar'gIntrigue 12
Aug26-591Lga 5½ f 1:05⅗ft 41 115 74¾ 74¾ 9111116 Sim'isG12 Mdn 75 JetTiger118 Maleficent118 SeafairQu'n 12
May25-593E.P a 3½ f :42⅕sy 3 *118 8 89½ 88¼ MarshW7 Mdn 79 GwenethGl'n111 TigerTh'ry118 B'byJoe 8
April 27 BM 3-8 sy :37h March 23 BM 3-8 ft :36⅗h March 19 BM 3-4 ft 1:15⅗hg

Tillies Baby 110 Br. f, 3, by Star Traveler—Till Lykke, by Boxthorn.
Breeder, A. L. Holmes. 1960 1 M 1 0 $425
Owner, A. L. Holmes. Trainer, A. Peters. $5,000 1959 1 M 0 0 ——
May10-601B.M 6 f 1:11⅗ft 9¼ 110* 11 14 14 2nk F'zierB2 M5000 85 Pilikia115 TilliesBaby110 Continuity 12
Jly 9-597Pln 5 f :59⅘ft 12 118 14 12 934 935 M'yh'nB5 AlwM 57 Imatz118 Kenty'sLover115 FrenchFilly 9
May 5 BM 3-4 ft 1:15⅘h April 29 BM 5-8 ft 1:01⅕h April 18 BM 3-8 ft :36hg

Past Performances—First Race at Bay Meadows on May 13, 1960

Figure 1. A past-performance chart.

PREDICTOR NAME

3	WEIGHT TO BE CARRIED THIS RACE
24	1968; PERCENTAGE OF RACES IN WHICH HORSE FINISHED FIRST,SECOND,OR THIR
55	WEIGHT HORSE CARRIED IN HIS LAST RACE
58	SPEED RATING CORRECTED BY TRACK VARIANT FOR HORSE'S LAST RACE
83	IS THE JOCKEY ONE OF THE LEADING JOCKEYS IN THIS RACE?

RACE 2 5 PREDICTORS

orse's number→	1	2	3	4	5	6	7	8
3	116	116	113	112	111	109	116	116
24	0	50	100	0	50	33	40	50
55	111	112	110	114	110	111	116	116
58	93	95	91	75	90	92	94	96
83	NO	YES	NO	NO	YES	YES	NO	YES

Figure 2. Example of one judge's information set in the 5 predictor condition.

Figure 3. The same judge's information set in the 40 predictor condition.

5

	PREDICTOR NAME
3	WEIGHT TO BE CARRIED THIS RACE
24	1968: PERCENTAGE OF RACES IN WHICH HORSE FINISHED FIRST,SECOND,OR THIRD
55	WEIGHT HORSE CARRIED IN HIS LAST RACE
58	SPEED RATING CORRECTED BY TRACK VARIANT FOR HORSE'S LAST RACE
83	IS THE JOCKEY ONE OF THE LEADING JOCKEYS IN THIS RACE?
19	1968: NUMBER OF STARTS
49	NUMBER OF DAYS SINCE HORSE'S LAST RACE
62	NUMBER OF LENGTHS HORSE FINISHED BEHIND LEADER IN LAST RACE
72	SPEED RATING OF HORSE CORRECTED BY TRACK VARIANT IN NEXT-TO-LAST RACE
76	SPEED RATING OF HORSE CORRECTED BY TRACK VARIANT ON SECOND-TO-LAST RACE
5	CLAIMING PRICE THIS RACE
12	HIGHEST CLASS AT AQUEDUCT THIS SEASON
33	1967: PERCENTAGE OF RACES IN WHICH HORSE FINISHED FIRST,SECOND,OR THIRD
47	RANK IN PACE RATING CORR, FOR WT.: BEST RACE THIS YR, AT "A" AT 6F ON FAST TRACK
52	CLASS OF HORSE'S LAST RACE
61	FINISHING POSITION OF HORSE IN LAST RACE
66	NUMBER OF DAYS SINCE NEXT-TO-LAST RACE
68	CLASS OF HORSE IN NEXT-TO-LAST RACE
73	NUMBER OF DAYS SINCE SECOND-TO-LAST RACE
51	WAS HORSE'S LAST RACE RUN AT AQUEDUCT?
1	AGE
2	SEX
8	HIGHEST CLASS ON HORSE'S PAST PERFORMANCE CHART
12	HIEST CLASS AT "A" THIS YR AT 6F W/ FINISH 1,2,3,4 OR W/IN 1/2 LENGTH OF LEADER
20	1968: NUMBER OF WINS
25	1968: TOTAL MONEY WON
28	1967: NUMBER OF STARTS
29	1967: NUMBER OF WINS
34	1967: TOTAL MONEY WON
37	NUMBER OF RACES IN LAST 21 DAYS
40	DISTANCE AT WHICH HORSE HAS RACED MOST OFTEN
41	FASTEST SPEED RATING ON PAST PERFORMANCE CHART FOR RACES OF 6F
54	DISTANCE OF HORSE'S LAST RACE
63	NUMBER OF LENGTHS GAINED OR LOST IN THE STRETCH IN LAST RACE
65	DID HORSE FAIL TO GAIN ON THE LEADER AT ANY CALL IN THE LAST RACE?
67	DISTANCE OF NEXT-TO-LAST RACE
78	DISTANCE OF LAST WORKOUT
79	TIME OF LAST WORKOUT
80	NUMBER OF DAYS SINCE LAST WORKOUT
88	IS THE TRAINER ONE OF THE LEADING TRAINERS IN THIS RACE?

Table 1

Test-Retest Consistency at Low (5 Predictors) and High (40 Predictors) Levels of Information for 8 Subjects (Horse Racing Study)

Index of Reliability	5 Predictors	40 Predictors
1. Changes in first-place selections	9/40 22%	14/40 39%
2. Changes in any of five ranks	91/200 45.5%	121/200 60.5%
3. Differences in ranks*	153	220

*Sum of differences is less for 5 than for 40 predictors in 30/37 races (3 ties)

Conclusion: Expert handicappers are much less consistent with 40 predictor items than with 5 predictor items.

Example: Race N: 5 predictors

	Horse numbers				
First ranking of Race N:	8	3	7	2	4
Second ranking of Race N:	7	3	4	8	2

The first-place horse changed; the horses changed at four out of five ranks; sum of differences = 3+0+2+1+2=8.

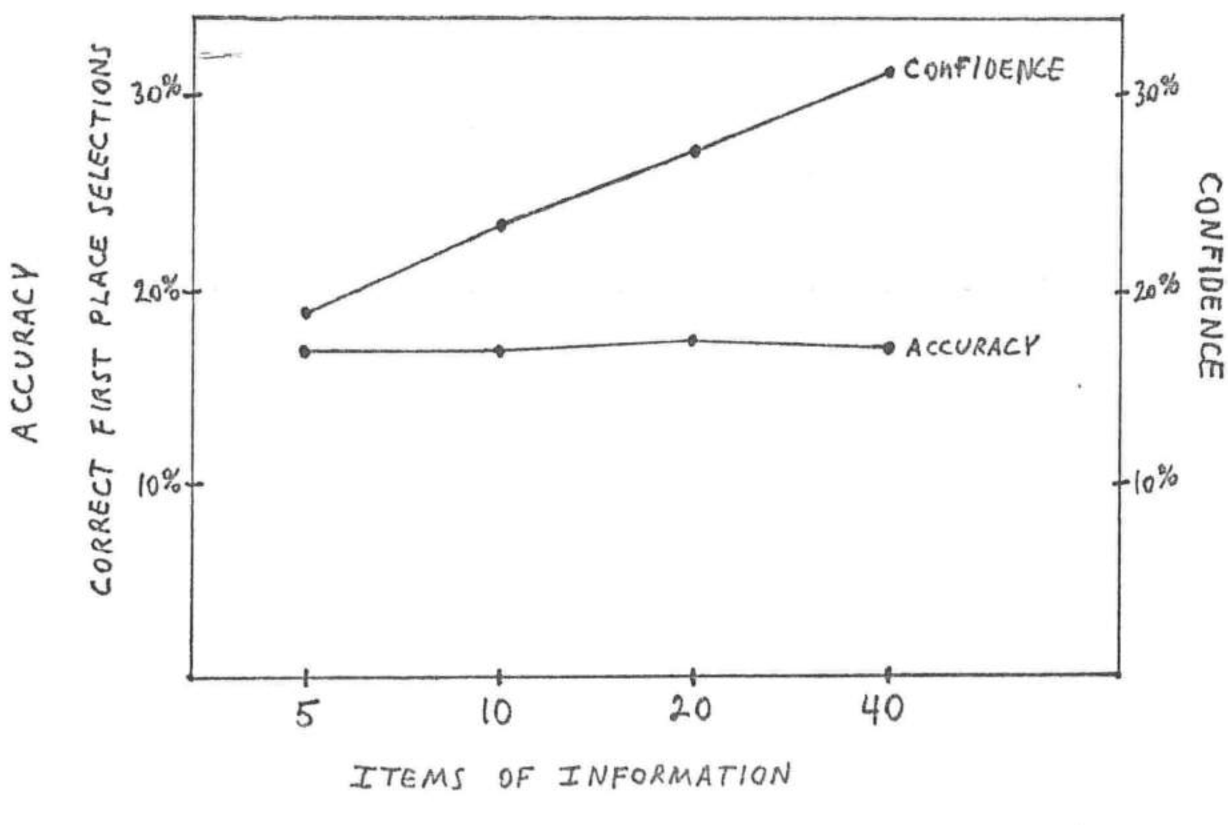


Figure 4. Mean changes in confidence and accuracy with increasing amounts of information.

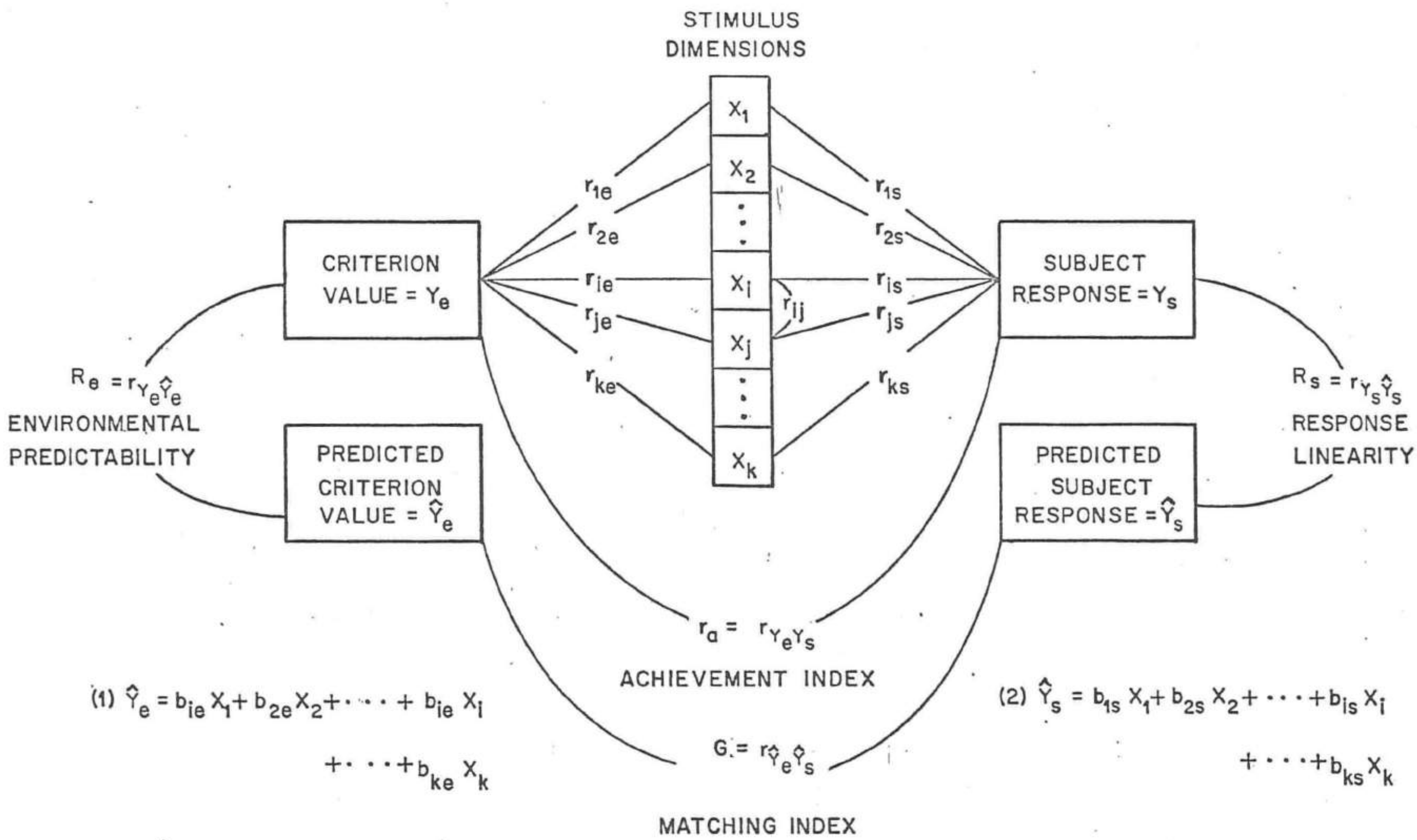


Figure 5. The lens model

b. method of analysis: the "lens model" (see Figure 5)

1. $r_a = r_{Y_e Y_s}$ — achievement
2. $G = r_{\hat{Y}_e \hat{Y}_s}$ — policy validity (appropriateness of judge's weights and function forms)
3. $R_s = r_{Y_s \hat{Y}_s}$ — policy consistency (random error)--index of control
4. $R_e = r_{Y_e \hat{Y}_e}$ — environmental consistency
5. $r_a = G R_s R_e$ — the lens model equation

c. results

1. subjects gain knowledge of nonlinear policies but predict poorly (low r_a) due to high degree of inconsistency (low R_s - lack of control) in executing the policy.

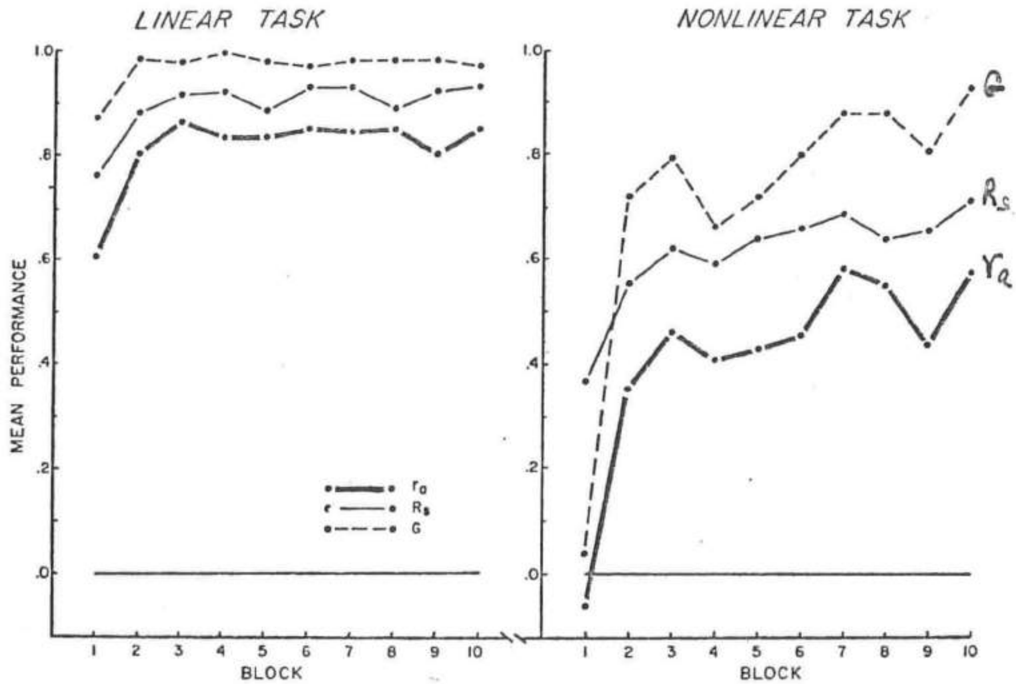


FIG. 6. Indexes of achievement (r_a), knowledge (G), and control (R_s) in two multiple-cue probability learning tasks. (In each task condition, $n = 20$.)

From Hammond & Summers (1972)

2. Outcome feedback impedes control over the execution of one's knowledge in the nonlinear task. (Hammond, Summers, & Deane, 1973)

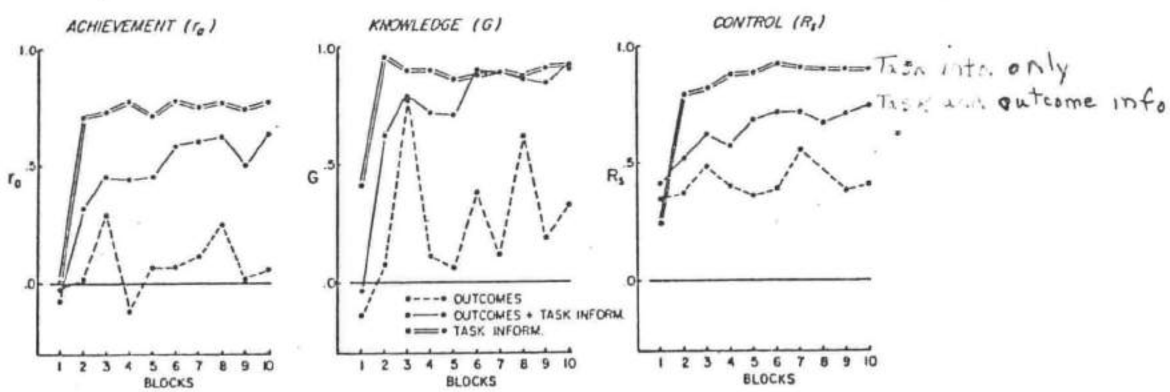


FIG. 7. Mean achievement (r_a), knowledge (G) and control (R_s) indices plotted over blocks of 20 trials according to experimental condition.

3. Brehmer (1971) finds that, even when you tell Ss what weights and functional relationships to employ, they have difficulties being consistent.

C. Systematic biases

1. general hypothesis

Man's limited memory, attention, and reasoning capabilities lead him to apply simple strain-reducing strategies when processing information. While these strategies may be efficient in some situations, in others they induce systematic biases that make the decision maker's actions inconsistent with his "true" preferences or beliefs.

2. Examples a, b, & c. Influence of response mode upon risk-taking decisions

a. When subjects rate the attractiveness of playing a gamble, probability of winning is the most important determiner of their responses; when they estimate the monetary worth of a gamble, payoff dimensions are more important than probabilities (Slovic & Lichtenstein, 1968).

TABLE 2

Percentage of Ss for Whom a Given

Risk Dimension Was Most Important

	Risk Dimension			
	P_W	$\$_W$	P_L	$\$_L$
Computed Weights				
Rating Group (N=88)	50	09	15	26
Bidding Group (N=125)	18	19	10	53
Subjective Weights				
Rating Group (N=43)	45	13	26	16
Bidding Group (N=50)	40	18	24	16

b. Given pairs of bets such as those below, subjects in Las Vegas often chose to play Bet A rather than Bet B, but they attached a higher monetary worth to Bet B. Such inconsistencies reflect systematic bias intervening between "true values" and observed preferences. They result from subjects using different information-processing strategies when choosing and setting prices.

Bet A	Bet B
11/12 chance to win 12 chips	2/12 chance to win 79 chips
1/12 chance to lose 24 chips	10/12 chance to lose 5 chips

where each chip is worth 25¢.

c. Individuals' preferences for long-shot bets were assessed by two methods: choices and selling prices--some persons gave selling prices consistent with their choices; others did not (see Figure 8).

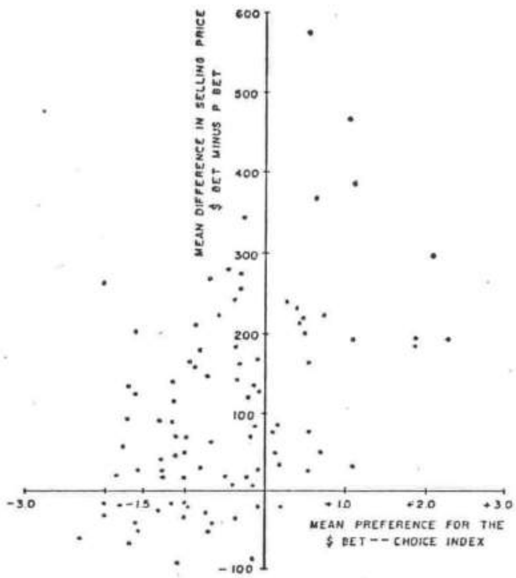


FIG. 8. Relationship between choice and selling-price indexes across the total sample of subjects ($r = .46$).

3. Slovic & MacPhillamy found that dimensions common to each alternative in a choice had greater influence upon decisions than dimensions that were unique to a particular alternative, even though the judges did not wish this to occur.

Table 3

Examples of Stimulus Pairs in the

Equal- and Unequal-Units Conditions

Common Dimension	Unequal-Units Condition			Equal-Units Condition		
	Student →	A	B	Student →	A	B
	NAch	67	59	NAch	618	561
NAch	Eng	___	86	Eng	___	572
	Quant	452	___	Quant	382	___
		A	B		A	B
	NAch	___	33	NAch	___	458
Eng	Eng	119	90	Eng	457	800
	Quant	414	___	Quant	348	___
		A	B		A	B
	NAch	___	27	NAch	___	698
Quant	Eng	74	___	Eng	469	___
	Quant	701	466	Quant	264	388

4. The experiments described above suggest that the compatibility or commensurability between a cue dimension and the required decision affects the importance of that cue in determining the decision.

5. biased perceptions of probabilistic events--"the law of small numbers"

   Tversky & Kahneman (1971) observed that people have strong intuitions about random sampling; these intuitions are shared by naive persons and sophisticated scientists, and they are wrong in fundamental ways with resulting unfortunate consequences in the course of scientific inquiry. They concluded that the typical scientist:

   a. has undue confidence in early trends from the first few data points and in the stability of observed patterns;

   b. rarely attributes a deviation of results from expectations to sampling variability because he finds a causal explanation for any discrepancy.

   These results suggest that investors may be too quick to infer that their policies are not working and too quick to change policies to remedy this apparent (but often illusory) failure.

D. Insight into one's own policy

Judges' insight into their own weighting policies is poor. They typically overestimate their weightings of minor cues and fail to recognize the extent to which their judgments can be predicted by only a few cues. Greater experience in the task may lead to poorer self-insight (see Figure 9 and Table 4, taken from Slovic, Fleissner, & Bauman, 1972).

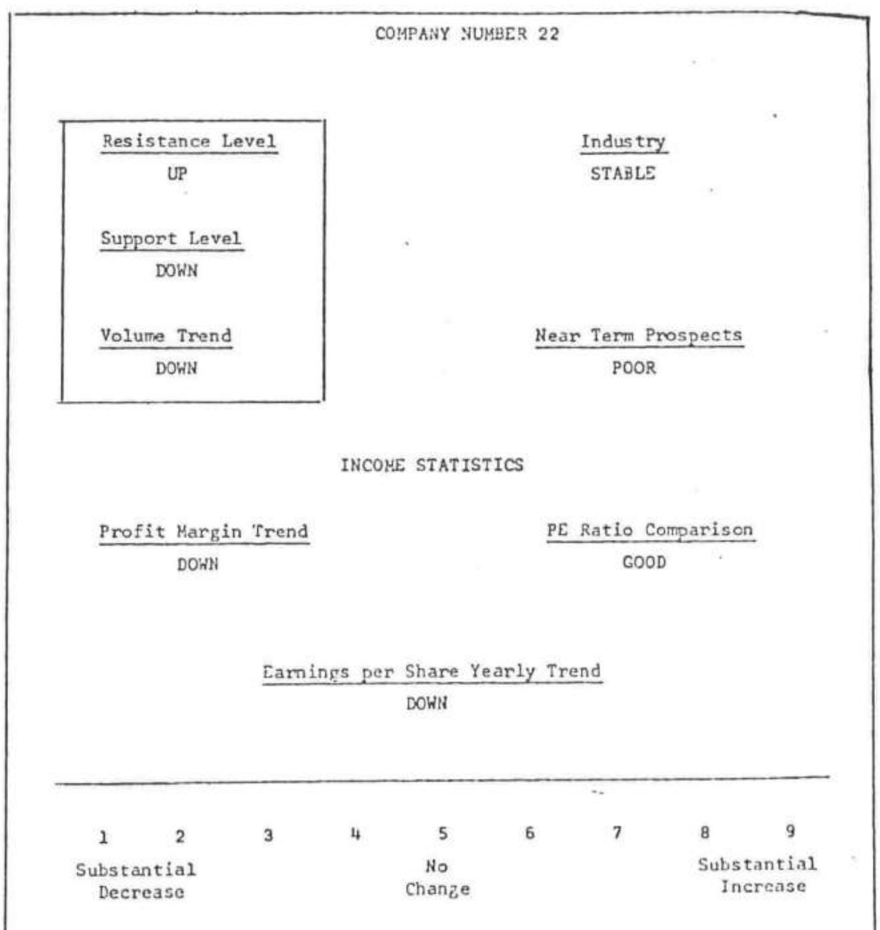


FIG. 9.—Example of a stimulus company. The response scale is at the

Table 4

Comparison between Importance of Effect and Subjective Weights across Thirteen Brokers and Five Students

Factor	Broker No. 1	2	3	4	5	6	7	8	9	10	11	12	13	Mean for Brokers	Student No. 1	2	3	4	5	Mean for Students
Importance of effect:																				
IND	02	01	09	09	07	03	10	04	04	13	10	14	03	07	03	10	14	04	12	09
RES	12	18	06	01	15	01	09	13	14	06	13	01	03	09	01	11	01	08	05	05
SUPP	**20**	28	06	05	07	11	06	15	07	10	**21**	02	06	11	03	04	06	05	01	04
VOL	16	07	08	13	08	14	06	**18**	13	17	07	02	04	10	14	07	04	02	00	05
NTP	16	07	**27**	**34**	13	14	**25**	16	22	**25**	09	11	15	18	13	07	15	14	00	10
PMT	09	05	05	02	11	20	14	09	10	09	11	24	22	12	13	18	10	17	10	14
PER	13	02	24	14	03	07	09	12	02	09	14	15	23	11	04	12	16	22	33	17
EYT	12	**32**	14	22	**36**	**31**	21	13	**28**	09	14	**32**	**24**	**22**	**48**	**29**	**34**	**29**	**39**	**36**
Subjective weight:																				
IND	**15**	**25**	10	15	10	**20**	15	**15**	13	15	10	10	15	14	10	03	**20**	09	18	12
RES	08	06	05	00	05	10	10	**15**	08	05	**20**	**20**	05	09	00	01	05	07	03	03
SUPP	08	06	06	00	05	10	10	**15**	08	05	**20**	**20**	10	09	00	01	05	07	03	03
VOL	12	20	09	20	10	15	15	05	15	15	**20**	15	10	14	20	05	15	10	03	11
NTP	12	04	**30**	**20**	10	10	**20**	10	**20**	15	05	05	**20**	14	13	10	05	12	15	11
PMT	10	04	05	05	10	15	07	**15**	05	10	05	10	10	08	08	25	10	12	15	14
PER	**20**	10	15	**20**	10	05	15	**15**	11	**20**	10	05	15	13	09	20	**20**	20	**22**	18
EYT	15	25	20	**20**	**40**	15	08	10	**20**	15	10	15	15	**18**	**40**	**35**	**20**	**24**	20	**28**

NOTE.—The highest entry in each column is in boldface type.

IV. Facilitating Adherence to Policy

A. If a decision maker is to approach subjective optimality (a condition wherein his actions are consistent with his underlying values and beliefs), random errors and systematic biases must be minimized.

B. Eliminating random error by "bootstrapping"

The judge's policy equation may do a better job of predicting some outcome or implementing the judge's personal values than the judge himself could do.

". . . humans tend to generate 'correct' strategies but then, in turn, fail to use their own strategy with any great consistency. ... One is left with the conclusion that humans may be used to generate inference strategies but that once the strategy is obtained the human should be removed from the system and replaced by his own strategy [Dudycha & Naylor, 1966]."

C. Analytic thinking--the decomposition principle

"The spirit of decision analysis is divide and conquer: Decompose a complex problem into simpler problems, get your thinking straight in these simpler problems, paste these analyses together with a logical glue, and come out with a program for action for the complex problem. Experts are not asked complicated, fuzzy questions, but crystal clear, unambiguous, elemental, hypothetical questions [Raiffa, 1968]."

D. Cognitive feedback

Hammond (1971) demonstrates that computerized feedback, showing the judge how his judgment policy compares to the desired policy, leads to dramatic increases in ability to execute a policy with consistency and precision. (See Figures 10, 11, and 12.)

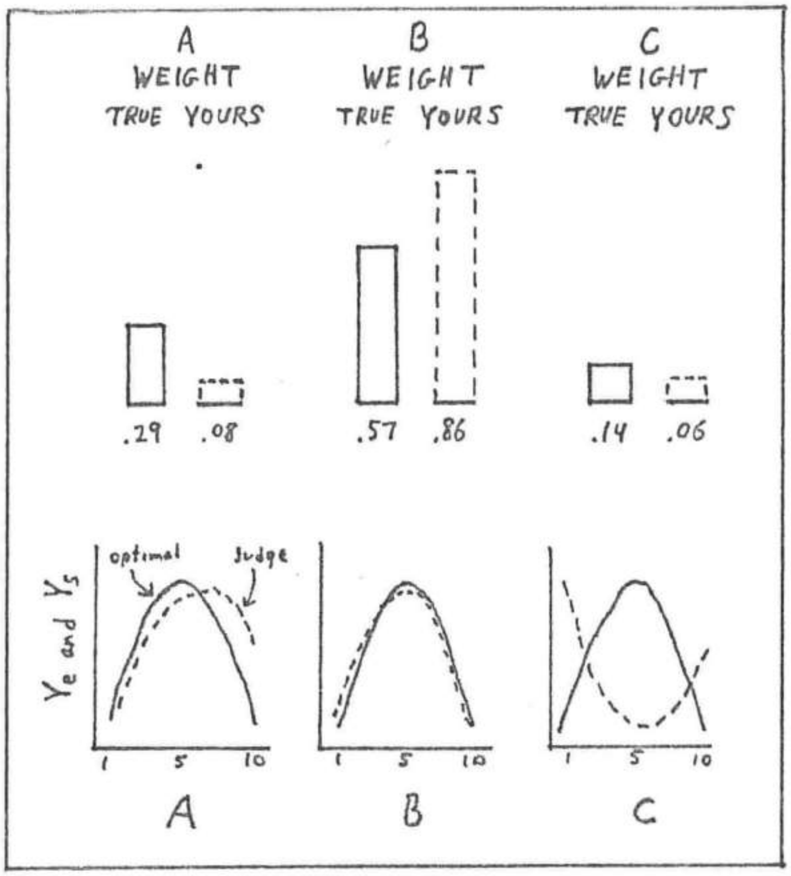


Figure 10. Cognitive feedback displays for a multiple-cue learning task.

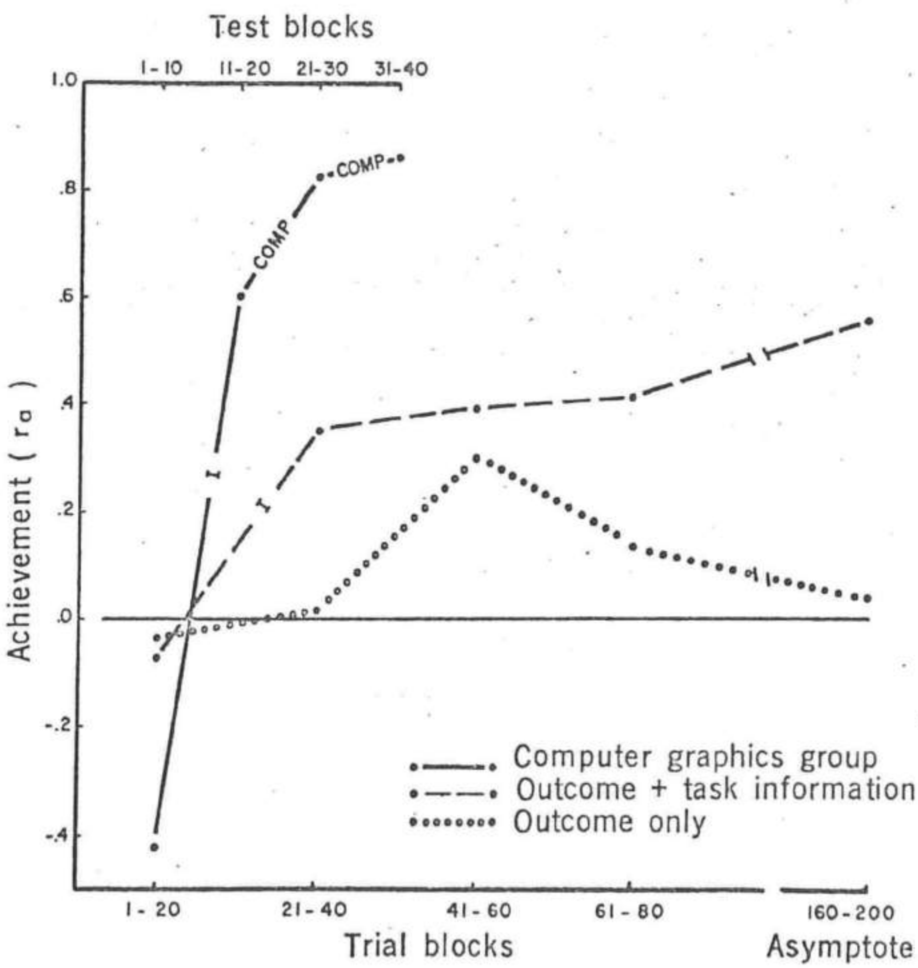


Figure 11. Learning curve for computer graphics group compared with groups receiving other forms of feedback.

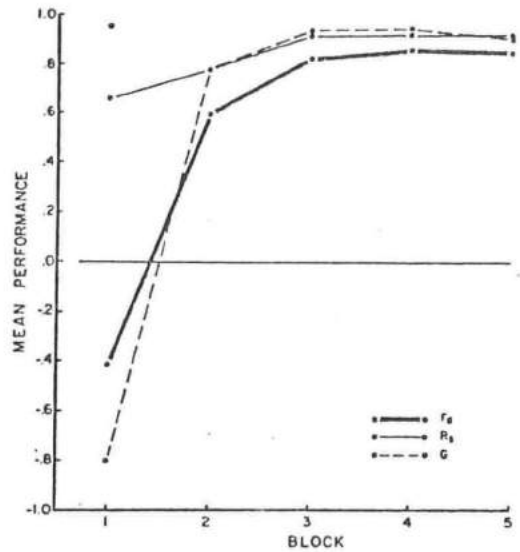


FIG. 12. Indexes of achievement (r_a), knowledge (G), and control (R_s) in a nonlinear inference task when cognitive feedback is presented in the form of graphic displays. (Block = 10 trials.)

V. References

A. A general introduction to this type of research is provided in the article: Slovic, P. Psychological study of human judgment: Implications for investment decision making. The Journal of Finance, 1972, 23, 779-799.

B. I will be happy to supply additional references for the work described in this talk.