Behavioral Problems of Adhering to a Decision Policy

Paul Slovic

Oregon Research Institute, Eugene, Oregon

"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 sterns 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

4

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.

Selected References

Brehmer, B. Subjects' ability to use functional rules. <u>Psychonomic Science</u>, 1971, 24, 259–260.

Dudycha, L. W., & Naylor, J. C. Characteristics of the human inference process in complex
choice behavior situations. <u>Organizational Behavior and Human Performance</u>, 1966, 1,
110–128.

Edwards, R. D., & McGee, J. <u>Technical analysis of stock trends</u>. Springfield, Mass.: John
McGee, 1966.

Garland, L. H. Studies of the accuracy of diagnostic procedures. <u>American Journal of
Roentgenology, Radium Therapy, and Nuclear Medicine</u>, 1959, 82, 25–38.

Goldberg, L. R. Man versus model of man: A rationale, plus some evidence, for a method of
improving on clinical inferences. <u>Psychological Bulletin</u>, 1970, 73, 422–432.

Hammond, K. R. Computer graphics as an aid to learning. <u>Science</u>, 1971, 172, 903–908.

Hammond, K. R., Summers, D. A., & Deane, D. H. Negative effects of outcome feedback in
multiple-cue probability learning. <u>Organizational Behavior and Human Performance</u>,
1973, 9, 30–34.

McGlothlin, W. Stability of choices among uncertain alternatives. <u>American Journal of
Psychology</u>, 1956, 69, 604–615.

Raiffa, H. <u>Decision analysis</u>. Reading, Mass.: Addison-Wesley, 1968.

Slovic, P. Information processing, situation specificity, and the generality of risk-taking
behavior. <u>Journal of Personality and Social Psychology</u>, 1972, 22, 128–134. (a)

Slovic, P. Psychological study of human judgment: Implications for investment decision making.
<u>Journal of Finance</u>, 1972, 27 , 779–799. (b)

Slovic, P., Fleissner, D., & Bauman, W. S. Analyzing the use of information in investment

  decision making: A methodological proposal. <u>Journal of Business</u>, 1972, 45, 283–301.

Slovic, P., & Lichtenstein, S. Comparison of Bayesian and regression approaches to the study of

  information processing in judgment. <u>Organizational Behavior and Human Performance</u>,

  1971, 6, 649–744.

Slovic, P., & MacPhillamy, D. Dimensional commensurability and cue utilization in comparative

  judgment. <u>Organizational Behavior and Human Performance</u>, in press.

Tversky, A., & Kahneman, D. The belief in the "law of small numbers." <u>Psychological Bulletin</u>,

  1971, 76, 105–110.

BEHAVIORAL PROBLEMS OF ADHERING TO A DECISION POLICY

Paul Slovic

Oregon Research Institute; Eugene, Oregon

". . . 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

----

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

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

   3   3 cues $\begin{Bmatrix} X_1, X_2, \& X_3 \\ A, B, \& C \end{Bmatrix}$ 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 $Y_e = .4A + .8B + .2C + \text{Error}$

   nonlinear $Y_e = .4(\alpha_1 A^2 + \alpha_2 A + \alpha_3) + .8(\alpha_1 B^2 + \alpha_2 B + \alpha_3) +$
   $.2(\alpha_1 C^2 + \alpha_2 C + \alpha_3) + \text{Error}$
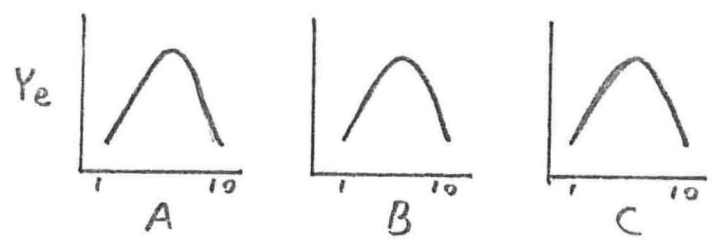
Function Forms in Nonlinear Task

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.

Owner, Mr. & Mrs. G. G. Jamieson. Trainer, L. W. Kidd. $5,000   1960   3 M 0 0 ———   1959   0 M 0 0 ———

May11-60	1B.M	6 f 1:12⅖ft 56	113	1½ 2h 2² 54¾ ScheihF³	M5000 76 VegasBoy118 Gasperlee118 PioneerJoe 12
Apr27-60	1B.M	6 f 1:13⅖sy 73	108* 4¾ 5⁹ 7¹⁵10¹⁷ D'l'gE¹²	M6500 59 L'leSpinet114 Tr'scribe118 T'xasT'b'ine 12
Mar15-60	1B.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 :36⅖h   May 2 BM 3-8 ft :35½h   April 26 BM 5-8 ft 1:03⅖b

Royal Jane

115 Ch. f, 3, by Texas Sandman—Fighting Jane, by Silver Horde.
Breeder, O. J. Todd.

Owner, Mr. & Mrs. E. H. Sorrell. Trainer, J. Weatherington. $5,000   1960   4 M 0 0 $125   1959   0 M 0 0 ———

May 4-60	5B.M	6 f 1:12⅖ft 40	113	4³½ 5²½ 55 58¾ Harm'zW⁸	5000 70 Starl'tTow'r108 Q'tWaters112 Wahalis 8
Apr26-60	1B.M	6 f 1:11⅕ft 9¾	115	5²½ 73¼ 78½ 7¹¹ PierceD³	Mdn 76 MissJoyce110 Himalaya115 Heione 12
Mar31-60	1B.M	6 f 1:12 ft 173	113	14 1² 1h 43½ PierceD²	4000 79 Q'tWaters112 Facetieux113 BernO'Dine 12
Mar25-60	1B.M	6 f 1:11⅘ft 53	108	10⁴¾ 87½ 8¹¹ 8¹² ShirotaM⁵	3500 72 HighDrag112 EdwardJ.114 RareToubo 12

April 20 BM 5-8 ft 1:01⅗h   April 10 BM 3-8 ft :36⅓h   March 23 BM 1-2 ft :49h

Bold Dust

115 B. f, 3, Bold Gallant—Garara, by Nirgal.
Breeder, E. J. Harris.

Owner, E. & J. Harris. Trainer, F. Jolosky. $5,000   1960   3 M 0 0 ———   1959   2 M 0 0 $40

May 4-60	2B.M	6 f 1:12⅖ft 251	114	5¾ 10¹⁴10¹⁴10¹⁴ HuntG¹	Mdn 66 Minnigerode118 HearYe118 Zipper-Bee 12
Apr28-60	1B.M	6 f 1:14 sl 182	115	2¹½ 45 5⁹ 6¹² HuntG¹⁰	Mdn 61 Sals-R'ge115 Sm'lT'wnGirl115 Kylew'd 12
Apr14-60	1B.M	6 f 1:11⅘ft 99	114	85¼10¹⁰10¹¹10¹⁹ HuntG⁷	Mdn 65 GoHost118 Principillo118 FoxyRudy 11
Sep23-59	5Pom	a 6 f 1:14⅕ft 24	116	8⁶½ 8⁹ 7⁹ 6¹⁶ Cant'iJ⁴	M5000 66 Dimity115 MissGenelle116 SunC. 8
Sep 3-59	1Dmr	6 f 1:11⅖ft 88	116	10¹²11¹⁹11¹⁸11¹⁸ 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.

Owner, Mr. & Mrs. N. C. Archer. Trainer, N. C. Archer. $5,000   1960   11 M 0 3 $485   1959   7 M 1 1 $302

May10-60	4B.M	6 f 1:12 ft 32	115	8⁷ 88¾ 55 34¾ HuntG⁶	M5000 76 Facetieux110 FlowerDeck115 Adagio 12
Apr 2-60	1B.M	6 f 1:10⅖ft 122	113	11⁷¾11⁸¾10¹⁴10¹⁵ GlennP⁹	4500 74 Stencil116 ArmedMiss116 DarkSh'dows 11
Mar17-60	1B.M	1¹/₁₆ 1:45⅕ft 50	113	8⁷¾10¹⁷10²⁴10²⁷ Gl'nnP¹⁰	M5000 51 Unrestr'ned113 K'rnPr'ss113 Brok'nL've 11
Mar10-60	1B.M	6 f 1:12⅕ft 25	113	11⁵¾10⁵¾ 5¹⁰ 67¾ GlennP⁴	M5000 75 Pr'ssG'ki114 Chic'oMiss108 Unrestr'ned 12
Mar 5-60	1B.M	6 f 1:12 ft 27	107	8⁴½ 57¾ 6¹³ 6⁹¾ GlennP⁵	3500 73 Reg'lGl'a109 Capt'nBos'n113 Q'tWaters 9
Feb22-60	3TuP	5½ f 1.06 ft 8½	115	52¾ 64 52¾ 54¼ Dittf'chH⁴	Mdn 80 TribalSec't120 Fr'tyBomb115 Unwritt'n 12
Feb17-60	3TuP	5½ f 1:12⅖ft 5½	113	55 55½ 76¼ 8⁷ FreyP¹⁰	M3500 76 JakeH'grass120 Ete'lLiz115 Time'sLast 12
Jan20-60	3TuP	6 f 1:13 ft 3½	110*11¹³ 8¹¹ 35 2³ Mu'yK¹²	M2500 77 PanchoDee120 Quico120 NowOn 12
Jan17-60	1TuP	5½ f 1:08⅗gd 3¾	115	73¼ 54 4¾ 44¼ Dittf'chH³	Mdn 68 WingLo115 Transcribe115 BullCamp 10
Jan 8-60	1TuP	6¼ f 1:19⅖ft 25	110* 73¼ 73¼ 3¼ 3¼ MurrayK³	Mdn 76 Jean'sChes't120 Directly120 Transcribe 10

May 6 BM 5-8 ft 1:02⅖hg   April 25 BM 3-4 ft 1:16⅖h   April 21 BM 3-8 ft :36⅖h

Painted Pet

115 Ch. f, 3, by Mafosta—Gold Paint, by Gold Bridge.
Breeder, F. R. Graham.

Owner, Montrose Stable. Trainer, K. R. Darbyshire. $5,000   1960   2 M 0 0 ———   1959   8 M 0 1 $130

May10-60	4B.M	6 f 1:12 ft 7¾	115	2¹ 3² 43½ 6¹⁰ Art'rnJ⁵	M5000 73 Facetieux110 FlowerDeck115 Adagio 12
Apr21-60	1B.M	6 f 1:13⅖ft 30	113	9¹⁶10²¹10²⁹10²⁴ V'zkeM³	M5000 53 D'm'dMark118 Kitsimbanyi113 P'n'rJoe 12
Dec14-59	3B.M	6 f 1:13⅖ft 17	116	54 74½ 95¾ 85½ YakaR⁷	M5000 68 TurkishNight116 SunnyNote116 SunC. 12
Dec10-59	1B.M	6 f 1:13⅕ft 22	114	83½ 9⁴ 11²⁶11²⁷ YakaR¹¹	M5000 50 Slippery117 NoExit114 MarketSpecial 12
Jun29-59	2L.P	4½ f :53⅖ft 10	117	7 44 32½ 33 Rich'dson⁵	Mdn MyBoyJ'n113 FoxeeLucee110 TigerTh'y 10
Jun25-59	2L.P	4½ f :54⅕ft 5½	117	8 77½ 87½ 77 Cop'nollK²	Mdn BraveKni't113 FoxeeLucee110 Y'gRuf'n 10
Jun15-59	2L.P	4½ f :53⅖gd 5½	118	6 44 45 46½ Cop'nollK⁴	Mdn Ur-Mia118 AmcanCathy111 Kydette 9
May 8-59	3Tan	5 f 1:01⅖ft 15	117	73¼ 85½ 89¾ 79¾ V'zkeM⁹	M6000 78 BlueTish117 Nina deTejas117 Step'gBy 11
May 4-59	3Tan	5 f 1:00⅖ft 24	117	64½ 53¼ 43 78¾ Art'burnJ⁷	Mdn 82 Svalan117 Lady d'Arg't112 N'a deTejas 7
Apr20-59	3Tan	5 f 1:01 ft 8¾	115	1½ 2h 43½ 79½ V'zkeM²	M8000 79 MissJ'hnnieD.115 T'mO'Farrell118 Reins 11

May 9 BM 3-8 ft :35⅖h   May 5 BM 1-2 ft :48⅖hg   April 13 BM 5-8 ft 1:05bg

Continuity

115 Ch. f, 3, by Balsamo—Sunny Pharlara, by Sun Briar.
Breeder, O. R. Harrod.

Owner, Mr. & Mrs. N. Jensen. Trainer, N. Jensen. $5,000   1960   5 M 0 1 $375   1959   3 M 0 0 $25

May10-60	1B.M	6 f 1:11⅖ft 28	115	74¼ 56¼ 3⁷ 34¾ Art'rnJ⁶	M5000 80 Pilikia115 TilliesBaby110 Continuity 12
May 4-60	4B.M	1¹/₁₆ 1:45⅖ft 175	113	11 78¼ 7¹⁷ 8¹⁶ Art'burnJ⁵	Mdn 60 Peno118 Principillo118 EdenBelle 8
Apr28-60	1B.M	6 f 1:14 sl 18	115	96¾ 78¼ 6¹¹ 5¹² Ar'burnJ¹¹	Mdn 61 Sals-R'ge115 Sm'lT'wnGirl115 Kylew'd 12
Apr21-60	1B.M	6 f 1:13⅖ft 52	113	55¾ 54¾ 46½ 48¼ Art'rnJ⁷	M5000 67 D'm'dMark118 Kitsimbanyi113 P'n'rJoe 12
Mar29-60	4B.M	6 f 1:12 ft 110	113	85¾ 78½ 79¼ 7¹¹ Art'burnJ⁸	Mdn 72 KerryPiper118 Graphite118 Nightken 12
Sep 3-59	1Lga	5½ f 1:08⅖gd 59	115	108¼106½106½ 55¾ FreyP⁴	M5000 70 Warbr'k118 Mirac'l'm118 Dar'gIntrigue 12
Aug26-59	1Lga	5½ f 1:05⅖ft 41	115	74¾ 74¾ 9¹¹11¹⁶ Sim'isG¹²	Mdn 75 JetTiger118 Maleficent118 SeafairQu'n 12
May25-59	3E.P	a 3½ f :42⅕sy 3	118	8 89½ 88½ MarshW⁷	Mdn 79 GwenethGl'n111 TigerTh'ry118 B'byJoe 8

April 27 BM 3-8 sy :37h   March 23 BM 3-8 ft :36⅖h   March 19 BM 3-4 ft 1:15⅖hg

Tillies Baby

110 Br. f, 3, by Star Traveler—Till Lykke, by Boxthorn.
Breeder, A. L. Holmes.

Owner, A. L. Holmes. Trainer, A. Peters. $5,000   1960   1 M 1 0 $425   1959   1 M 0 0 ———

May10-60	1B.M	6 f 1:11⅖ft 9½	110* 11 14 14 2nk F'zierB²	M5000 85 Pilikia115 TilliesBaby110 Continuity 12
Jly 9-59	7Pln	5 f :59⅘ft 12	118	14 1² 934 935 M'yh'nB⁵	AlwM 57 lmatz118 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.

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
10	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.
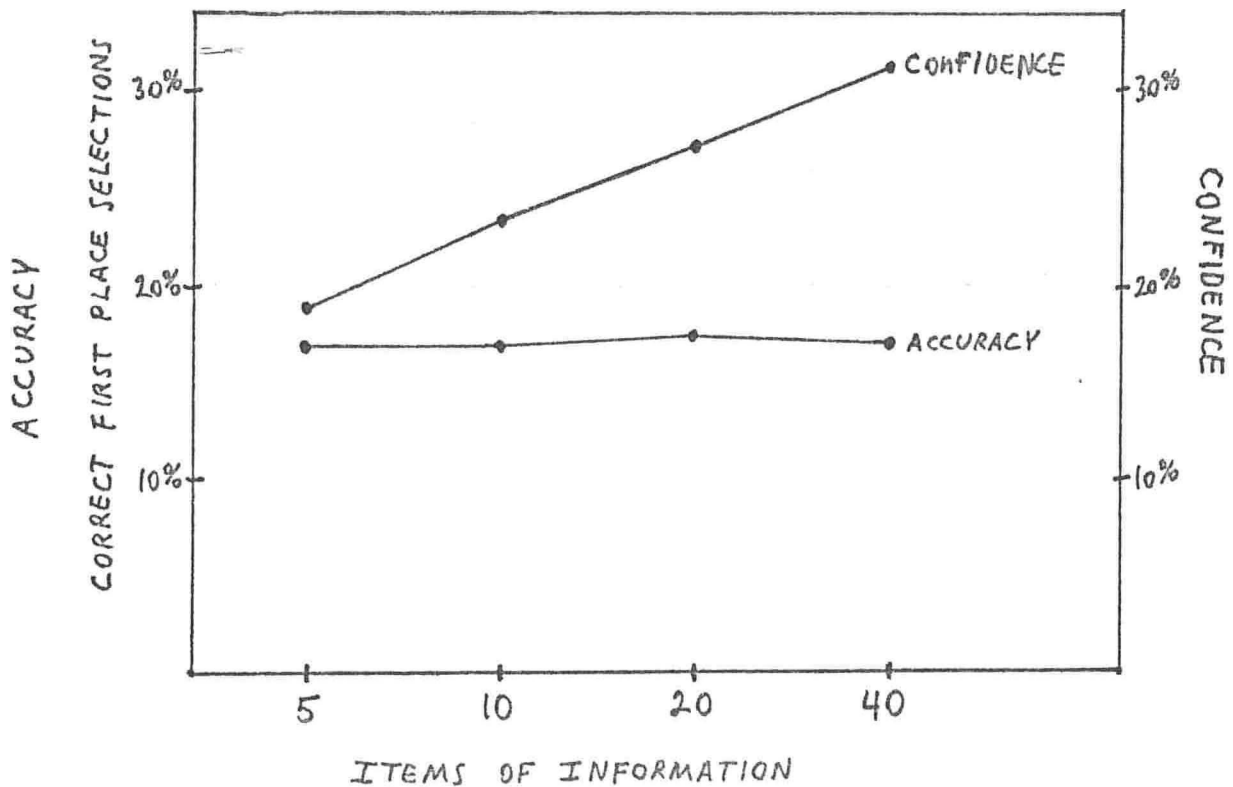
Figure 4.   Mean changes in confidence and accuracy with increasing amounts of information.

STIMULUS
DIMENSIONS

$$Y_e = \text{CRITERION VALUE}$$

CRITERION
VALUE = Y_e

SUBJECT
RESPONSE = Y_s

$R_e = r_{Y_e \hat{Y}_e}$

ENVIRONMENTAL
PREDICTABILITY

r_{1e} r_{1s}
r_{2e} r_{2s}
r_{ie} r_{is}
r_{je} r_{js}
r_{ke} r_{ks}

r_{ij}

X_1
X_2
$\vdots$
X_i
X_j
$\vdots$
X_k

$R_s = r_{Y_s \hat{Y}_s}$

RESPONSE
LINEARITY

PREDICTED
CRITERION
VALUE = $\hat{Y}_e$

PREDICTED
SUBJECT
RESPONSE = $\hat{Y}_s$

$r_a = r_{Y_e Y_s}$

ACHIEVEMENT INDEX

(1) $\hat{Y}_e = b_{ie} X_1 + b_{2e} X_2 + \cdots + b_{ie} X_i$

$+ \cdots + b_{ke} X_k$

$G = r_{\hat{Y}_e \hat{Y}_s}$

MATCHING INDEX

(2) $\hat{Y}_s = b_{1s} X_1 + b_{2s} X_2 + \cdots + b_{is} X_i$

$+ \cdots + b_{ks} X_k$

Figure 5.   The lens model

b. method of análysis: 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. $r_a = GR_s R_e$ 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.

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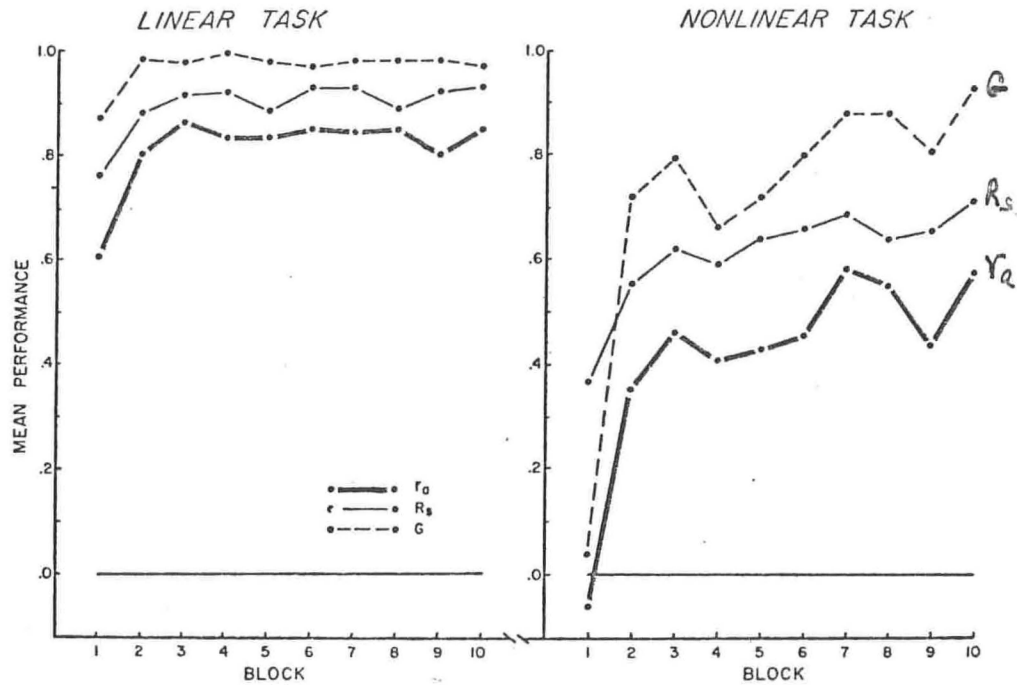
FIG. 6. Indexes of achievement (r_a), knowledge (G), and control (R_s) in two multiple-cue probability learning tasks. (In each task condition, $n=20$.)

From Hammond & Summers (1972)

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

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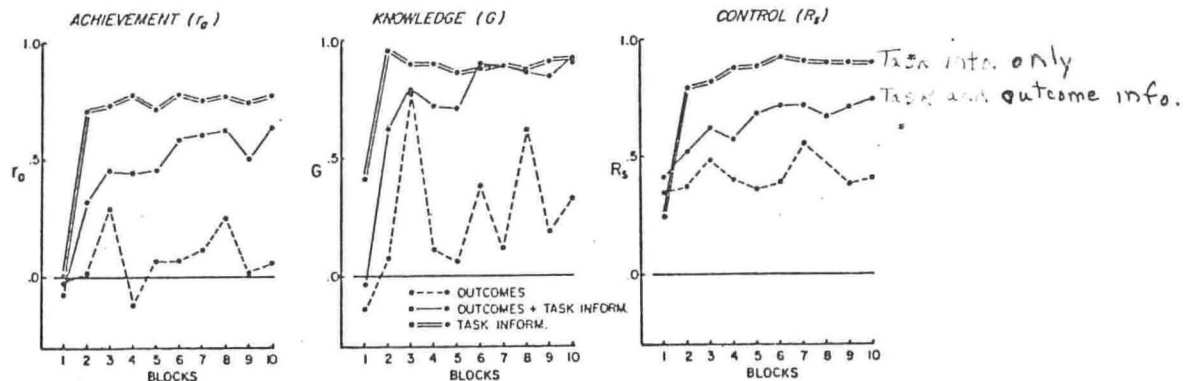
FIG. 7. Mean achievement (r_a), knowledge (G) and control (R_s) indices plotted over blocks of 20 trials according to experimental condition.

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
11/12 chance to win 12 chips
1/12 chance to lose 24 chips

Bet B
2/12 chance to win 79 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).
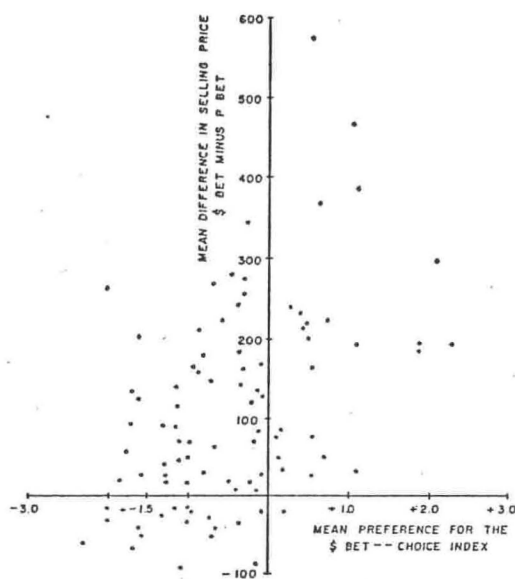
FIG. 8. Relationship between choice and selling-
price indexes across the total sample of subjects
($r = .46$).

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).


```
                         COMPANY NUMBER 22


        Resistance Level                    Industry
             UP                              STABLE

        Support Level
           DOWN

        Volume Trend                    Near Term Prospects
           DOWN                               POOR


                         INCOME STATISTICS


        Profit Margin Trend              PE Ratio Comparison
             DOWN                              GOOD



              Earnings per Share Yearly Trend
                         DOWN



     1     2     3     4     5     6     7     8     9
   Substantial              No                Substantial
    Decrease              Change                Increase
```
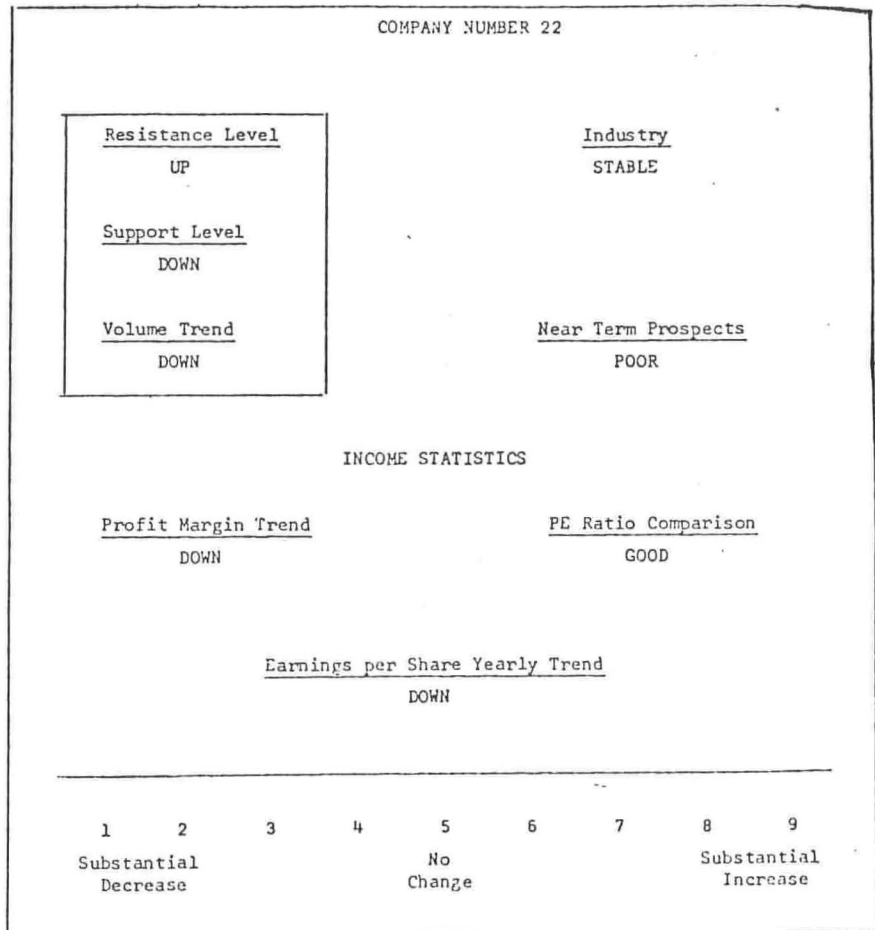
FIG. 9.—Example of a stimulus company. The response scale is at the

Table 4

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

Factor	Broker No.													Mean for Brokers	Student No.					Mean for Students
	1	2	3	4	5	6	7	8	9	10	11	12	13		1	2	3	4	5	
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.)
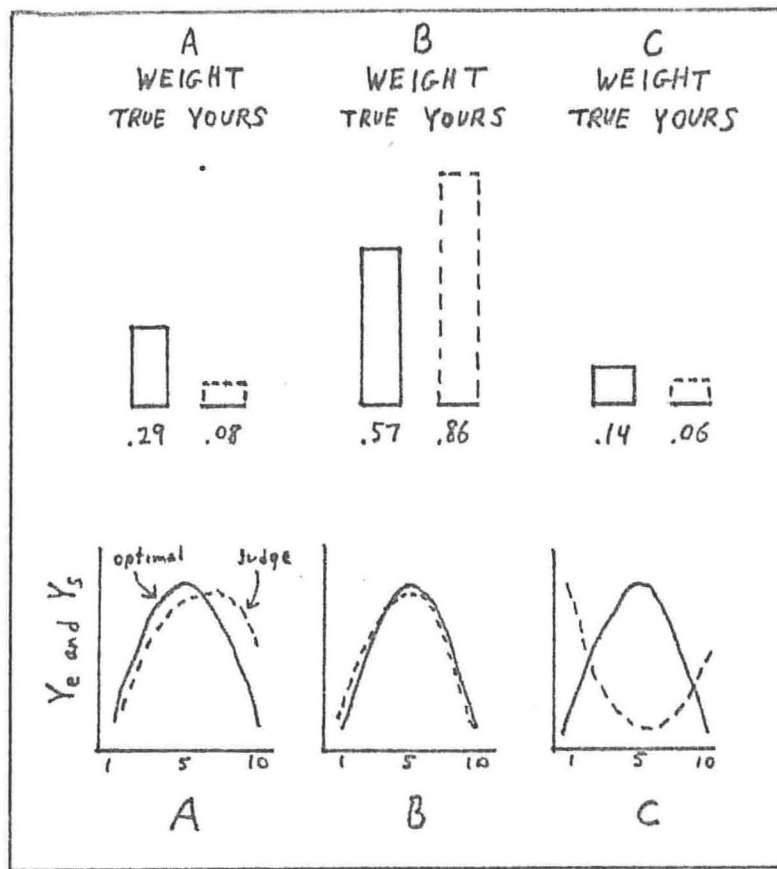
Figure 10. Cognitive feedback displays for
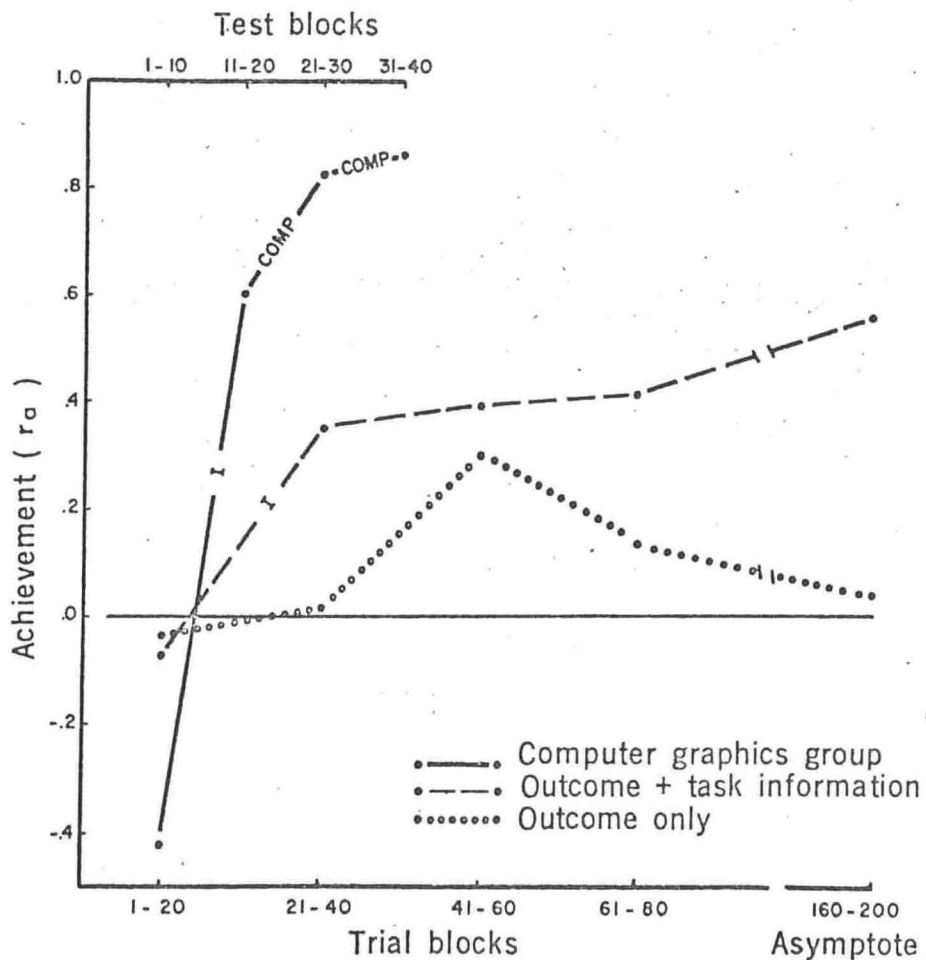a multiple-cue learning task.

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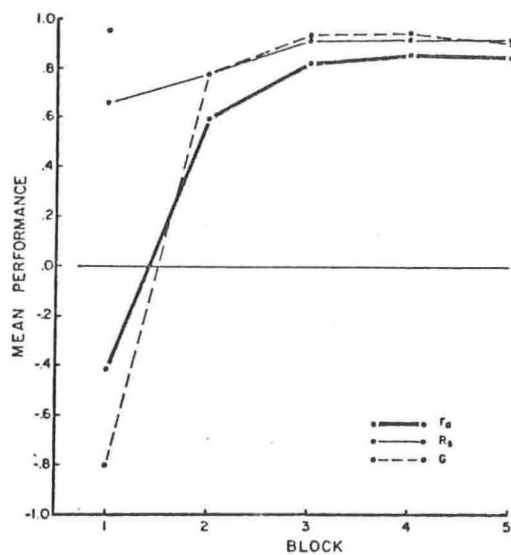with groups receiving other forms of feedback.

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.