

COGNITIVE CONTROL¹

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The theory developed here proposes that performance in cognitive tasks involves two distinct processes: acquisition of knowledge and cognitive control over knowledge already acquired. A conceptual and analytic framework is presented which allows for the disentanglement of knowledge and control, and for the quantification of each. Evidence from studies of multiple-cue probability learning, clinical judgment, and interpersonal conflict supports the theoretical usefulness of this framework and indicates that poor performance in cognitive tasks can often be attributed to incomplete cognitive control, rather than incomplete knowledge. The importance of cognitive feedback—as opposed to traditional outcome feedback—for the development of cognitive control is illustrated.

Although learning theorists have long emphasized the distinction between learning and performance, little attention has been given to skill in the application of knowledge in tasks which do not involve motor performance. Rather, there is an implicit assumption that once knowledge has been acquired, the application of this knowledge is largely dependent on certain experimental circumstances.

For example, Deese and Hulse (1967) point out that

sometimes we have good reason to believe that an organism is simply not demonstrating what it has learned because we have not chosen the proper conditions which will assure the overt display of the appropriate behavior [p. 62].

Leeper (1970) makes a similar point, but draws attention specifically to motivational factors:

One of the distinctive points of cognitive learning theory—a principle developed by Lashley (1929), Tolman (1932), and others—is that a clear distinction must be made between learning (or the “acquisition of habits”) and performance (or the “use of

habits”), and that a good share of the “use of habits” depends on current motivation [p. 287].

Other theorists, also stressing the importance of distinguishing between learning and performance, have suggested additional determinants of the application of knowledge; for example, fatigue (Hilgard, 1956) and instructions (Mandler, 1967). Indeed, Mandler goes somewhat further and suggests that a distinction be made between “the conditions under which a subject will discover a particular rule [and] his *abilities* to use . . . it [p. 22; italics added].”

Although the explanations for the inappropriate application of knowledge mentioned above are by no means identical, they are (with the exception of Mandler) quite similar in one important respect. Specifically, they all assume that the potential for full *application* of knowledge accompanies full *acquisition* of knowledge—except in psychomotor tasks.

The position taken here, however, is that acquisition and application are independent components of learning in cognitive tasks as well as psychomotor tasks. Consequently, we argue that the development of skill—or control—in the application of knowledge already acquired is a matter to be investigated. The purpose of this paper, therefore, is to introduce the concept of cognitive control, to indicate its theoretical and methodological context, and to illustrate its empirical significance in studies of human learning, judgment, and interpersonal behavior. In addition, traditional

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outcome feedback is identified as an impediment to the development of cognitive control.

THEORY

Fundamental to our treatment of cognitive control is a methodological and conceptual framework developed for studying behavior in multiple-cue probability learning tasks. A major reason for the emphasis on multiple-cue probability learning tasks is the fact that such tasks have essential features in common with a broad range of inference tasks human subjects routinely encountered outside the laboratory. Aside from this, there are two additional reasons for studying the problem of cognitive control in the framework of multiple-cue probability learning tasks: (a) Multiple-cue probability learning tasks can be varied sufficiently in complexity and uncertainty so that both knowledge and cognitive control can be varied extensively, and (b) quantitative separation of knowledge and control has been accomplished within this framework.

Variations in Complexity and Uncertainty

Multiple-cue probability learning tasks can be varied in both complexity and uncertainty in at least three ways: (a) the number of cues related to a criterion can be varied, (b) the uncertainty associated with each cue can be varied by creating differential cue validities, and (c) the form of the relation between cue and criterion can be varied; either positive linear relations, negative linear relations, or various non-linear relations may be used (see Brehmer & Lindberg, 1970; Knowles, Hammond, Stewart, & Summers, 1971; Naylor & Clark, 1968; Sheets & Miller, in press; Summers, 1969; Summers & Hammond, 1966; Uhl, 1963).

Quantitative Denotation of Knowledge and Control

The analysis of multiple-cue probability learning has typically been carried out within the Brunswikian framework (Brunswik, 1956) as modified by Hammond (1966). As illustrated in Figure 1, Brun-

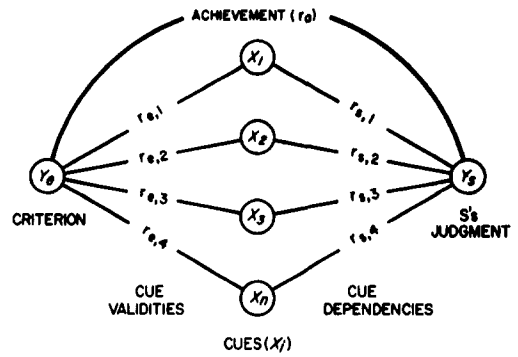


FIG. 1. Brunswik's lens model.

wik's "lens model" has been used to convey a pictorial model of the relation between subject and task. The mathematical specification of the relation between cue validities and cue dependencies in Figure 1 was introduced by Hursch, Hammond, and Hursch (1964), and modified in various ways subsequently (Dudycha & Naylor, 1966; Rozeboom, 1971; Tucker, 1964). Tucker's (1964) development of the lens model equation will be used here. It reads as follows:

$$r_a = GR_cR_s + C \sqrt{1-R_c^2} \sqrt{1-R_s^2} \quad [1]$$

where

- r_a = the correlation between Y_c and Y_s ;
- G = the correlation between the linear prediction of Y_c and Y_s from the cue values;
- R_c = the multiple correlation between the cues and Y_c ;
- R_s = the multiple correlation between the cues and Y_s ;
- C = the correlation between the variance in the task system and the subject's judgmental system which is unaccounted for by the linear component G .

When the systematic variance in the criterion can be accounted for by a linear function of the cue values, then the contribution of the second term on the right-hand side of Equation 1 will be negligible. Equation 1 then reduces to

$$r_a = GR_cR_s \quad [2]$$

Equation 2 may, of course, be applied to nonlinear functions in the case where the appropriate transformation can be effected—as in all the studies described below. It is Equation 2 that makes the distinction between knowledge and control most apparent. Therefore, each term in Equation 2 is discussed separately below.

r_a (achievement): This term measures performance; specifically, r_a represents the covariation of the subject's judgments (Y_s) with the criterion (Y_c).

G (knowledge): This term measures the extent to which the subject has correctly detected properties of the task. Specifically, this term reflects the covariation between the least-squares prediction of the criterion (\hat{Y}_c) and the least-squares prediction of the subject's judgments (\hat{Y}_s) from the cues. When systematic task variance can be identified and represented in a regression equation, G denotes the degree to which the subject's cognitive system is isomorphic with the task system independent of uncertainty in the task system (R_s) or control in the subject's response system (R_c).

Isomorphism as used here does not, of course, imply identity; G may reach unity, as it should, when the regression coefficients in the task system and the subjects cognitive system are proportional (see Castellan, 1971).

R_s (task uncertainty): This term measures the predictability of the criterion (Y_c) from the cues (X_1) in the task system. It sets a limit on the extent to which achievement (r_a) may occur, even if knowledge (G) and control (R_c) are perfect (see Hursch et al., 1964, also Hammond, Hursch, & Todd, 1964, for a discussion of the limits of achievement under conditions of uncertainty). R_s , of course, may be determined by the experimenter.

R_c (cognitive control): This term measures the extent to which the subject controls the execution of his knowledge; it indicates the predictability of the subject's response (Y_s) from the cues (X_1). Note that R_c is statistically independent of G . Such independence is critical, for it means that even should G reach unity (indicating

perfect knowledge), if R_c were less than unity (indicating imperfect control), performance would be less than the limit of achievement (R_s) would permit. Conversely, R_c might equal 1.00, thus indicating that the perfectly controlled cognitive system was not appropriate to the task system, thus preventing achievement (r_a) from reaching its upper limit (R_s).

Two subjects, therefore, might have identical achievement indexes for different reasons; one because of perfect knowledge ($G = 1.00$) but imperfect control ($R_c < 1.00$) and the other because of perfect control ($R_c = 1.00$), but imperfect knowledge ($G < 1.00$). Variations between these extremes could also occur, of course.

APPLICATIONS OF THE THEORY

Applications of the theory will be illustrated in regard to (a) individual learning in complex, multiple-cue inference tasks, (b) clinical judgment, and (c) conflict between two persons working together in a multiple-cue probability learning task.

Individual Multiple-Cue Probability Learning

In a recent experiment (Deane, Hammond, & Summers, 1972), subjects were studied in two three-cue probabilistic tasks: one in which the relation between each cue and the criterion was *linear*, and one in which the relation between each cue and the criterion was *nonlinear*. It should be noted that previous research involving nonlinear inference tasks has shown the learning of nonlinear relations to occur slowly, if at all (see Brehmer, 1969; Hammond & Summers, 1965). Typically, the poor performance observed in complex nonlinear tasks is attributed to an inability of most subjects to detect the task relation—in short, poor performance is usually explained in terms of the subject's inability to acquire full knowledge of these tasks.

In the effort to evaluate the role of control, however, Deane et al. (1972) provided subjects in both the linear and nonlinear task conditions (after 20 warm-up trials) with the knowledge necessary for highly

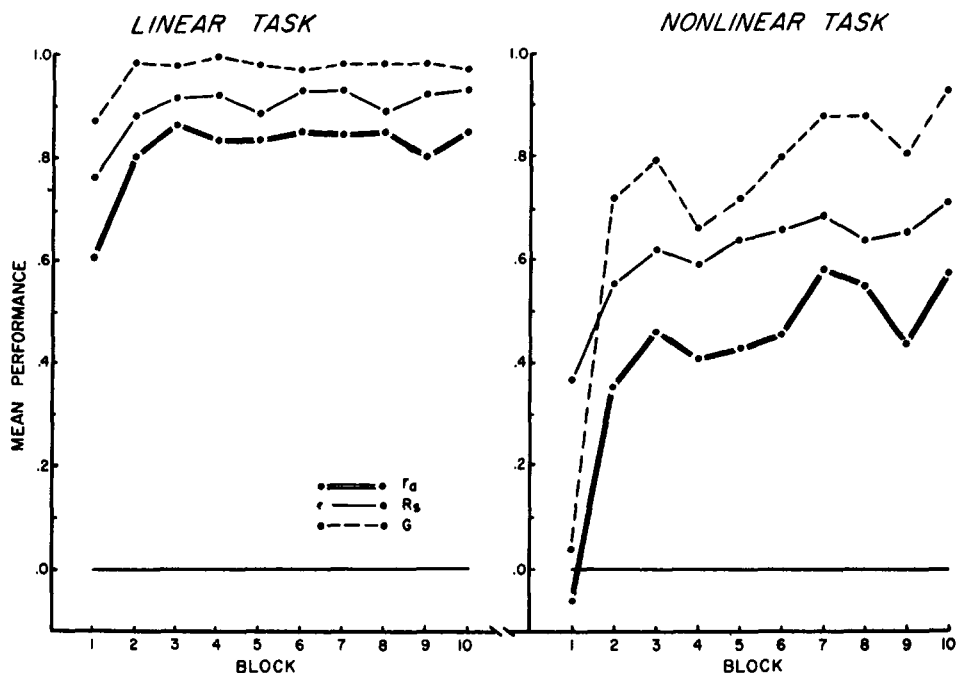


FIG. 2. Indexes of achievement (r_a), knowledge (G), and control (R_s) in two multiple-cue probability learning tasks. (In each task condition, $n=20$.)

accurate performance; that is, subjects were told how each cue was related to the criterion dimension and how each cue should be weighted. Moreover, this information was provided to the subjects in two different ways; verbally or pictorially. Following each learning trial, the subject was given the usual outcome feedback; that is, the subject was informed of the correct answer.

The results of this experiment indicated that poor performance in complex inference tasks (e.g., those involving nonlinear relations) can be attributed to difficulties in cognitive control, as well as to difficulties in acquiring knowledge about the task. At the conclusion of training (200 trials), the level of predictive accuracy (r_a) achieved by subjects in the nonlinear task condition was significantly lower than that achieved by subjects in the linear task condition (.58 and .84, respectively). Yet, as can be seen in Figure 2, knowledge, as measured by G , was essentially the same in these two tasks by the end of training. In contrast, however, cognitive control

(R_s) was far below optimal for subjects in the nonlinear task, even after 200 trials. For subjects in the linear task condition, control (R_s) was hardly distinguishable from knowledge (G).

These findings indicate that knowledge and control can be disentangled empirically, as well as statistically, and demonstrate that even when knowledge is complete, imperfect cognitive control can prevent high achievement.

It is important to note that the findings summarized above are not peculiar to tasks involving probabilistic cue-criterion relations; that is, irreducible error. For example, Brehmer (1969) studied performance in four different multiple-cue tasks—all permitting perfect accuracy ($R_s = 1.00$)—and found considerable differences according to the type of task relation the subjects were required to learn and use. When the criterion was a simple linear function of the cues ($Y_c = X_1 + X_2$), the subjects had little difficulty in rapidly achieving a high level of performance. When the task required the subjects to utilize a complex

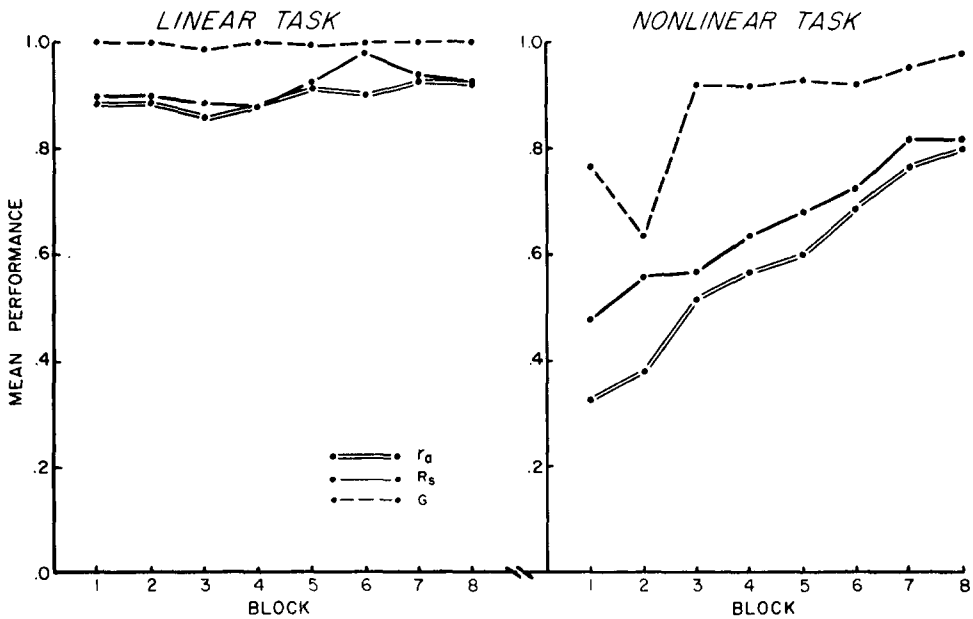


FIG. 3. Indexes of achievement (r_a), knowledge (G), and control (R_s) in two multiple-cue learning tasks in which perfect achievement is possible. (In each task condition, $n = 10$.)

nonlinear function ($Y_e = X_1/X_2$), however, performance was generally poor and improved quite slowly.

One plausible explanation for Brehmer's findings is, of course, that the subjects in the latter condition were unable to detect the task relations; that is, that subjects were unable to acquire the appropriate task knowledge. As can be seen in Figure 3, however, a reanalysis of his data using the framework proposed here suggests quite a different explanation. Note that in the linear task, both knowledge (G) and control (R_s) were high; as a consequence, performance (r_a) was near perfect. In contrast, performance (r_a) in the nonlinear task improved slowly, and remained significantly ($p < .01$) below that attained in the linear task—even at the end of 400 trials. The R_s and G curves, however, indicate that this poor performance in the nonlinear task cannot be attributed solely to the subjects inability to learn the task relations. Indeed, G improved rapidly, and at the conclusion of training was virtually indistinguishable from that attained by subjects in the linear task (.98 and .99, respectively). The primary source of the

suboptimal performance in the nonlinear task was lack of full cognitive control over knowledge acquired; that is, R_s improved far more slowly than did G , and remained significantly ($p < .05$) less than that attained in the linear task at the conclusion of training (.78 and .90, respectively).

Cognitive Control in Clinical Judgment

The analyses described above illustrate the usefulness of *cognitive control* as an explanatory concept in laboratory studies of human learning. There is growing evidence that this concept is also useful in accounting for performance in nonlaboratory situations as well—such as those involving clinical judgment.

Several investigators of judgment processes (e.g., Dudycha & Naylor, 1966; Ward & Davis, 1965) have argued that judgment policies (in a variety of domains) are frequently "correct" (implying high G), but are executed in an inconsistent manner (implying low R_s). This point has been elaborated by Goldberg (1970) who made use of Tucker's version of the Lens Model Equation to demonstrate how clinical

judgment is influenced by inconsistency; that is, by failure of control. Specifically, Goldberg reanalyzed the judgments of 29 clinical psychologists about 861 Minnesota Multiphasic Personality Inventory profiles and found that while G was typically high ($G = .68$), judgmental accuracy was low ($r_a = .28$).

Although there is evidence that this poor performance was partially due to an inability to detect nonlinearity in the judgment tasks, there is also evidence that it resulted from lack of control; that is, low R_s . For when Goldberg produced *perfect control* by replacing the clinical judge with a perfectly consistent linear model (in effect setting $R_s = 1.0$), performance (r_a) improved for 86% of the judges. Similar findings have been reported by Dawes (1971) in a study involving judgments made by graduate admissions committees.

These results support Dudycha and Naylor's (1966) contention that

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 [p. 127].

The results also confirm our views concerning the theoretical distinction between knowledge and control.

Cognitive Control and Interpersonal Conflict

There is evidence that the framework proposed here is significant not only for individual performance, but for certain kinds of two-person interactions as well. Of particular concern here are those interpersonal conflicts (quarrels) which arise when two persons must exercise their judgments under conditions of uncertainty. Such quarrels are studied in settings in which two or more individuals who have learned to utilize probabilistic cues in quite different ways (different cue weights and/or different function forms) are required to reach joint agreement in multiple-cue probability learning tasks.

A large number of studies have investigated the conflict, or disagreement, which

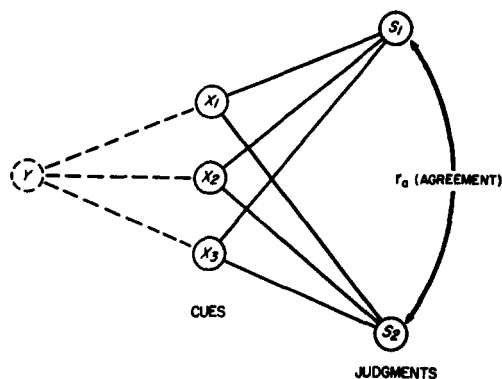


FIG. 4. Brunswik's lens model as applied to the two-person case. (Note that characteristics of the judgment task are represented on the left, while characteristics of each person's cognitive system are represented on the right.)

arise under these conditions, and all have found that the reduction of conflict occurs slowly, if at all, even when subjects are given outcome feedback which clearly indicates to each that his cognitive system is inadequate (Hammond & Brehmer, in press). A commonsense explanation suggests that the slow reduction in conflict merely reflects the reluctance of most people to alter their beliefs (even in the face of contradictory evidence). Examination of conflict behavior using the theoretical analysis proposed here, however, points to a different interpretation.

Such analysis is enhanced by the fact that not only can each subject's behavior be examined in relation to an environmental task system, but each subject's behavior can also be examined in relation to the response system of the other (Hammond, Wilkins, & Todd, 1966). As can be seen in Figure 4, the theoretical framework outlined earlier—including the concept of cognitive control—is directly applicable to this type of interpersonal situation as well as to the individual learning and judgment tasks described above: r_a represents agreement between the responses of the two subjects, G represents the convergence between the two systems, and R_1 and R_2 represent the cognitive control exerted by S_1 and S_2 , respectively.

The results from interpersonal conflict studies conducted in eight different nations

(see Brehmer, Azuma, Hammond, Kostron, & Varonos, 1970; Hammond & Brehmer, in press) have been analyzed in the above terms. The results of these studies all point in the same direction: the subjects' cognitive systems converged (G increased), but cognitive control diminished (R_s decreased) as a result of the interaction. Thus the quarrels—differences in judgments—continued despite increased agreement in principle (increased G); loss of cognitive control (decreased R_s) produced disagreement in fact. These results imply that cognitive control plays a significant part in interpersonal learning and conflict as well as in individual learning and clinical judgment.

FEEDBACK AND CONTROL

Why does cognitive control (R_s) exhibit such a slow growth curve relative to knowledge (G)? If subjects *know* what to do, why do they not apply their knowledge more effectively? The answer appears to lie in the heretofore unexamined traditional form of feedback in human learning experiments.

Outcome Feedback as an Impediment to Control.

As in the above experiments, it is customary to expect subjects to learn by providing them with the correct answer on every trial. But that tradition follows from an unexamined assumption which cognitive theory has inherited from trial and error and S-R theories of learning. Indeed, outcome feedback is still an integral part of the learning research paradigm used by all psychologists—even cognitive theorists.

Recently, however, it has become apparent that outcome feedback does not provide much help for subjects attempting to acquire knowledge about the properties of complex inference tasks, particularly when the task requires learning of complex relations under conditions of uncertainty (e.g., Todd & Hammond, 1965). Dramatic confirmation of this conclusion is provided by Goldberg (1968) who reported that even after 4,000 trials—each followed by out-

come feedback—learning in a complex clinical inference task was practically nonexistent.

Of equal importance, however, are numerous findings that the removal of outcome feedback typically results in an increase in response consistency (Azuma & Cronbach, 1966; Bjorkman, 1965; Brehmer & Lindberg, 1970). These findings suggest that in addition to its limited usefulness in the acquisition of knowledge, outcome feedback may be detrimental to control, as well.

Cognitive Material as Feedback

An alternative approach, more in keeping with cognitive theory, is to provide feedback that contributes to the exercise of control rather than feedback that prevents, or at least slows, the development of control. Feedback which contributes to control should consist of *cognitive* material—not *response*-oriented material—which will enable the subjects to perceive not only that their judgment was in error, but *why* it was in error. Such cognitively oriented feedback must enable the subject to compare (a) the properties of his cognitive system with (b) the properties of the task system with which he is trying to cope, whether a content-neutral learning task or the cognitive system of another person. Of particular importance in this respect are two essential parameters: (a) differential cue weights and (b) the form of the function relating each cue to the criterion.

The critical question is: Once the subjects have been given such feedback, can they exercise sufficient cognitive control (R_s) to increase their overall performance (r_a), without loss in their grasp of the properties of the task (G)? The results of two experiments indicate that they can.

The first of these studies (Todd & Hammond, 1965) employed two different probabilistic tasks in which the subject was instructed to use the information afforded by three geometric cues to predict a numerical criterion. One of these tasks, which required the subjects to weight all three cues equally, was particularly difficult to learn; performance in this task is therefore of primary interest here.

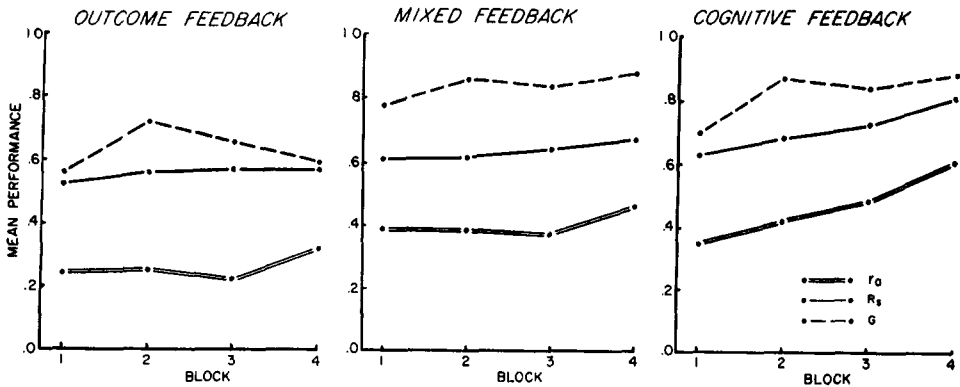


FIG. 5. Indexes of achievement (r_a), knowledge (G), and control (R_k) in a multiple-cue probability learning task under conditions of outcome, mixed, and cognitive feedback. (In each feedback condition, $n = 12$.)

The major innovation in this study is that one group of subjects received only cognitively oriented feedback during learning (referred to as "lens model" feedback by Todd and Hammond). Using an on-line computer arrangement, each subject was periodically given information about task properties (cue validities), as well as properties of his cognitive system (cue utilization coefficients). A second group was given only traditional outcome feedback; that is, the correct answer after every trial. A third group was given both cognitive and outcome feedback (referred to as "mixed" feedback).

Using r_a as a measure of performance, Todd and Hammond found that the group which received only cognitive feedback performed most accurately, followed by the mixed feedback group, and finally by the outcome feedback group. That the cognitive feedback group performed better than the outcome feedback group is theoretically gratifying; but what is surprising is that subjects who received both the cognitive and outcome feedback ("mixed" feedback) performed *less* well than subjects who were given lens model feedback only.

A reanalysis of the Todd and Hammond data revealed that performance in the mixed feedback conditions can be explicated in terms of cognitive control. As can be seen in Figure 5, subjects in both the cognitive and mixed feedback conditions were able to achieve a high degree of knowledge

about the task. The G indexes for these two groups were quite high throughout, and were near identical by the end of 200 trials. On the other hand, *control* in the cognitive feedback condition was significantly ($p < .01$) higher than in the mixed feedback condition, even at the end of training. (Note that neither knowledge nor control improved substantially in the outcome feedback condition.)

In short, the cognitively oriented feedback given to subjects in the cognitive and mixed feedback conditions facilitated the acquisition of knowledge about task properties. The addition of outcome feedback to the mixed feedback condition, however, served to *decrease* cognitive control and thus contributed to the suboptimal performance achieved by these subjects.

A second study employed the same non-linear judgment task used by Deane et al. (described earlier), but used an on-line computer graphics terminal as a means of providing feedback. This technique enabled the subject to compare periodically his cue weights and function forms with the properties of the task system in pictorial form. (Some practical implications of the rapid learning associated with computer graphics techniques are pointed out in Hammond, 1971.) Even though a small number of subjects was employed ($N = 5$), the experiment yielded clear results. Performance (r_a) reached the limit of achievement after two or three comparisons. It

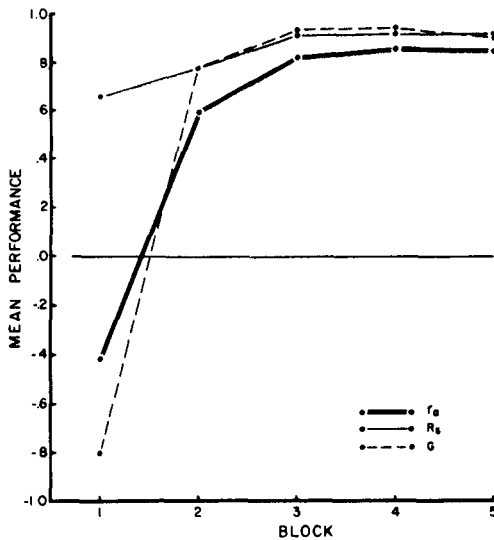


FIG. 6. Indexes of achievement (r_a), knowledge (G), and control (R_s) in a nonlinear inference task when cognitive feedback is presented in the form of graphic displays. (Block = 10 trials.)

should be noted that the acquisition of knowledge (G) by these subjects did not differ from that observed under outcome feedback conditions in the Deane et al. study; that is, G was near optimal in both experiments. When subjects received *only* graphics feedback, however, control (R_s) as well as G was high (see Figure 6). In short, feedback which provides the appropriate cognitive material permits cognitive control to be executed and overall performance to improve.

SUMMARY

Our purpose has been to demonstrate that cognitive control is a concept of theoretical significance, and that it is susceptible to quantification and experimental manipulation. In addition, when this concept is brought to bear on important cognitive matters—individual learning, clinical judgment, and interpersonal conflict—it leads to explanations of behavior which are meaningful and coherent across all three domains.

Furthermore, the evidence which suggests that traditional, response-oriented outcome feedback is an impediment to

cognitive control (and thus to performance) also points to the facilitating effect of *cognitive* material as feedback. This shift in conception of the notion of feedback carries considerable practical as well as theoretical significance, for it is now evident that computer technology can be used to produce such facilitating feedback. Therefore, it should be possible to improve performance in complex cognitive tasks in which improvement has heretofore been unlikely.

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