Toward a Unification of Psychophysical and Behavioural Research[1]

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Research reviewed here provides empirical support for a behavioural account of signal-detection performance which captures both stimulus and reinforcement effects. This model is based on the matching of response ratios to reinforcement ratios in the presence of discriminative stimuli. It provides for the quantification of stimulus effects in free-operant paradigms, and a better understanding of reinforcement effects in psychophysical studies. Other areas of investigation suggested by this approach are also discussed. These include the derivation of psychometric functions, memory, and the discriminability of schedules of reinforcement.

The recent introduction of behavioural models of signal-detection theory (Davison & McCarthy, 1980; Davison & Tustin, 1978; Nevin, Jenkins, Whittaker & Yarensky, Note 1) facilitates a unified account of the manner and degree to which the effects of both sensory and nonsensory variables combine to determine behaviour in a diversity of paradigms. In addition, these models provide the basis for a quantitative unification of three major areas of Experimental Psychology which have hitherto remained disparate: classical psychophysics, contemporary psychophysics (or, the theory of signal detection), and schedule-control research.

Classical psychophysics—the quantitative branch of the study of human and animal perception, investigating relations between sensory and physical continua—marks the beginning of Experimental Psychology. Central to psychophysics is the concept of the sensory threshold. In threshold studies, the psychophysicist seeks an index of his subject's sensory capacity either in terms of the minimum perceptible stimulus strength (defined as the absolute threshold), or the minimum perceptible difference between two stimuli (the differential threshold). The existence of a sensory threshold, and the utility of this construct as a cornerstone of psychophysics, has long been debated. Generally, it is believed that measures of stimulus sensitivity (or, thresholds) were contaminated by other nonsensory variables (e.g., attitudinal or motivational variables, collectively termed response bias), although the effect of these variables on threshold measurements has never been clearly delineated.

The development of the theory of signal detection marked the beginning of a more definitive solution to this problem. Rather than estimating a single sensitivity (threshold) parameter, signal-detection theory allows the extraction of two independent measures from data obtained in a psychophysical experiment. The two measures are stimulus discriminability, a measure of the subject's ability to tell two stimulus conditions apart, and response bias (or, criterion), a measure of how performance can be changed by nonsensory motivational or payoff variables.

Both classical psychophysics, and the more recent theory of signal detection, have placed primary emphasis upon the sensory performance of human subjects, and attempts to relate stimulus parameters to the physical properties of the stimuli

are well documented. As a result, less effort has been expended in the investigation of nonsensory variables.

In operant psychology, on the other hand, schedule-control research has examined behaviour as a function of nonsensory variables (e.g., reinforcement) with stimulus parameters usually held constant, and stimuli made clearly discriminable. The rules prescribing the relations between stimuli, responses, and reinforcers are known as schedules of reinforcement, and the performances they control have been the subject of extensive research in the experimental analysis of behaviour.

Operant-conditioning experiments with animals also provide the possibility of extensive and detailed investigation of both classical and contemporary theories of psychophysics. Psychophysical research with humans is commonly carried out under verbal instruction, and the effects of nonsensory variables (e.g., payoff, stimulus-presentation probability) are frequently influenced by these instructions, and by the past experience and reinforcement history of the subject. These effects are, however, particularly amenable to study with animals using operant methodology because all variables affecting behaviour may be explicitly specified and controlled. Verbal instructions, for example, are replaced, in animal research, by explicit contingencies of reinforcement.

However, while there is a very extensive literature documenting the application of psychophysical statistics to data obtained from operant-conditioning experiments, and operant methodology and analysis have become ubiquitous in animal psychophysics, quantitative relations between these areas have only recently been forthcoming. Psychophysics has provided us with an adequate understanding of stimulus effects, and we know many things about reinforcement effects from schedule-control research, but the traditions of psychophysical and behavioural research are different, and quantification has proceeded separately. For a complete understanding of behaviour, however, the study of stimulus and reinforcement effects should not proceed apart when each requires a consideration of the other.

This paper reviews an ongoing programme of research designed to complete the unification of psychophysical and behavioural research. The aim of the programme is two-fold. Firstly, to provide psychophysics with an adequate theory of response bias by clarifying the role of reinforcement in signal-detection experiments, and quantifying the effects of response bias on threshold measurements. The second part of the programme is addressed to the adequate measurement and understanding of stimulus effects in studies of choice and schedule control.

Behavioural models of signal-detection performance

The first step toward unification came with the application of laws governing choice behaviour on schedules of reinforcement to the signal-detection paradigm (Davison & Tustin, 1978; Nevin et al., Note 1). This novel approach showed how both stimuli and reinforcers combine to determine performance on signal-detection tasks.

The standard yes-no detection task is schematized in Figure 1. The subscripts W, X, Y, and Z refer to the cells of the
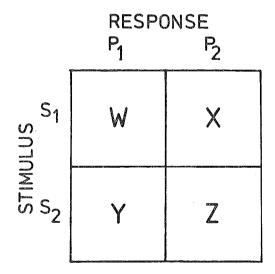

Figure 1. The matrix of events in a typical (yes-no) signal-detection procedure. One of two responses (P1, P2) is emitted following presentation of one of two stimuli (S1, S2). The cells of the matrix in which responses and reinforcements are tallied are denoted by W, X, Y, Z.

matrix, and P and R denote *numbers* of responses and reinforcements in each cell. The two discriminative stimuli, S1 and S2, may be related on the same physical dimension (e.g., two different light intensities), may be related by one having an additive property to the other (e.g., noise, signal-plus-noise), or may be unrelated. P1 and P2 are the two choice responses which the subject is trained to emit in the presence of S1 and S2, respectively (e.g., "yes, signal present" and "no, signal absent", or a left-key response and a right-key response). Correct responses are P1 in the presence of S1 (Pw, hits), and P2 in the presence of S2 (Pz, correct rejections). Incorrect responses are P2 in the presence of S1 (Px misses), and P1 in the presence of S2 (Py, false alarms). Reinforcers are typically given for correctly reporting S1 or S2 when they were present (reinforcers denoted Rw and Rz, respectively). Incorrect responses usually have no consequence (i.e., $Rx = Ry = 0$), or are punished in some way.

Davison and Tustin (1978) drew an anology between the matrix of events in the detection task (Figure 1), and that of two concurrent reinforcement-extinction schedules, each operating under a distinctive stimulus. That is, in the presence of S1, hits are reinforced while misses are not reinforced, and, in the presence of S2, correct rejections are reinforced but not false alarms.

Davison and Tustin's (1978) analysis was based on the large amount of data from concurrent-performance studies which show how behaviour is distributed between two concurrently-available alternatives as a function of the distribution of reinforcements for these alternatives. This research shows that response ratios in concurrent schedules of reinforcement are a power function of reinforcement ratios (Baum, 1974). In logarithmic form, this relation, known as the generalized matching law, is:

$$\log \left(\frac{Pm}{Pn}\right) = a \log \left(\frac{Rm}{Rn}\right) + \log c , \quad (1)$$

where Pm and Pn are the numbers of responses emitted in the two components, and Rm and Rn are the numbers of reinforcements obtained from the component

schedules. The exponent *a* reflects the *sensitivity* of the response ratio to changes in the ratio of obtained reinforcements (Lander & Irwin, 1968), and *log c* is *inherent bias* (Baum, 1974; McCarthy & Davison, 1979), a constant preference over all experimental conditions unaffected by changes in the obtained reinforcement distribution between the two alternatives. The generalized matching law holds for concurrent-schedule performance from rats and pigeons to man, with diverse reinforcers, and in a wide variety of experimental procedures.

In the signal-detection paradigm (Figure 1), the generalized matching law suggests that if the two stimuli, S1 and S2, are indistinguishable, the distribution of total left and right responses will be sensitive only to the ratio of reinforcements for left and right responses, that is Rw/Rz (Figure 1). Davison and Tustin (1978) suggested that, as the stimuli become more discriminable, performance would become progressively biased toward P1 in S1 and toward P2 in S2 (Figure 1). As biases are constant additive quantities in the logarithmic form of the generalized matching law (Equation 1), Davison and Tustin proposed separate generalized-matching-law equations to describe behaviour in the presence of each of the two stimuli in the detection task.

In the presence of S1,

$$\log \left(\frac{Pw}{Px}\right) = a \log \left(\frac{Rw}{Rz}\right) + \log d + \log c , \quad (2)$$

and, in the presence of S2,

$$\log \left(\frac{Py}{Pz}\right) = a \log \left(\frac{Rw}{Rz}\right) - \log d + \log c , \quad (3)$$

where P and R denote number of responses emitted and number of reinforcements obtained, respectively, and the subscripts refer to the cells of the matrix in Figure 1.

As in the generalized matching law, the parameter *a* is the *sensitivity* of behaviour to changes in reinforcement. The ratio of reinforcements quantifies a *reinforcement bias* (McCarthy & Davison, 1980b) arising from different numbers of reinforcements for left- and right-key responses (or,

different magnitudes of reinforcement, etc., McCarthy & Davison, 1979). This is a bias in the sense that ratios of left and right responses are determined by the overall left-to-right ratio of reinforcements (Rw/Rz), although, as in the generalized matching law, changing the reinforcement ratio will change behaviour with a certain sensitivity. The sensitivity parameter measures the relation between changes in a biaser and changes in behaviour. When one biaser is varied, and another is kept constant, precise estimates of both the values of the constant biaser, and the sensitivity with which behaviour changes with the varied biaser can be obtained. The reinforcement ratio is thus a biaser in the same sense as in signal-detection theory where, for example, the payoff matrix may be varied (i.e., criterion changed) to obtain an estimate of discriminability.

Log c is, as in the generalized matching law, *inherent bias,* a constant bias in S1 or S2 which may arise from the equipment (e.g., different forces required to operate response manipulandum), or from the subject itself, perhaps a preference for responding on the left key rather than on the right key. It remains invariant across experimental conditions. Reinforcement bias and inherent bias are the two sources of response bias (McCarthy & Davison, 1980b; in press).

Log d is the bias caused by the *discriminability* of S1 and S2. This bias is, of course, toward P1 in S1, and away from P1 in S2. The better the subject can discriminate S1 from S2, the larger will be log d, and so the larger the ratio Pw/Px and the smaller the ratio Py/Pz. Since the numerators in both Equations 2 and 3 are the P1 response category, log d is positive in Equation 2 and negative in Equation 3.

In the normative version of signal-detection theory, variations in stimulus parameters are presumed to affect only discriminability while variations in other nonsensory parameters (e.g., payoff) are presumed to affect only the location of the criterion (or, the degree of response bias). The Davison and Tustin (1978) model embodies this separation between the effects of sensory and nonsensory variables by assuming that the behavioural effects of

discriminability and reinforcement bias are additive in logarithmic terms (Equations 2 and 3), and hence, there is no interaction between these two variables.

We investigated empirically this assumption of independence by examining the biasing effects of changes in the obtained reinforcement ratio on the detection performance of pigeons for both an easy and a difficult discrimination (McCarthy & Davison, 1980b). We found the same positive slopes for Equations 2 and 3 at both levels of discriminability. This result implies (a) that reinforcement sensitivities are the same in the presence of each of the two stimuli (i.e., *a* in Equation 2 is equal to *a* in Equation 3) at both discriminability levels, and (b) the value of reinforcement sensitivity is unaffected by variations in discriminability. Hence, as assumed by Davison and Tustin (1978), there is no interaction between these two independent variables.

Equations 2 and 3 can, therefore, be used to specify how independent measures of stimulus discriminability and response bias can be obtained. As reinforcement sensitivities are the same in the presence of each stimulus, Equation 3 can be added to Equation 2 to remove the effects of discriminability:

$$\log\left(\frac{Pw}{Px}\right) + \log\left(\frac{Py}{Pz}\right)$$
$$= 2a\log\left(\frac{Rw}{Rz}\right) + 2\log c . \qquad (4)$$

This equation is called a *bias function* (McCarthy & Davison, 1980a) as it relates behaviour in the presence of the two stimuli to the combined effects of inherent bias (log c) and reinforcement bias. Thus:

$$a\log\left(\frac{Rw}{Rz}\right) + \log c$$
$$= .5\left[\log\left(\frac{Pw}{Px}\right) + \log\left(\frac{Py}{Pz}\right)\right] . \qquad (5)$$

We call the measure on the right side of Equation 5 *response bias* (McCarthy & Davison, 1979). The left side of Equation

5 specifies the environmental conditions which produce the response bias. A discriminability-free estimate of response bias is thus given by:

$$\text{response bias} = \left(\frac{Pw}{Px} \cdot \frac{Py}{Pz}\right)^{\frac{1}{2}} . \qquad (6)$$

Likewise, Equation 3 can be subtracted from Equation 2 to eliminate the effects of inherent bias and reinforcement bias on detection performance:

$$\log\left(\frac{Pw}{Px}\right) - \log\left(\frac{Py}{Pz}\right) = 2 \log d . \qquad (7)$$

We call Equation 7 a *stimulus function* (McCarthy & Davison, 1980a) because it relates behaviour to the discriminative stimuli independently of response bias. An estimate of discriminability, unaffected by response bias, is therefore given by:

$$d = \left(\frac{Pw}{Px} \cdot \frac{Pz}{Py}\right)^{\frac{1}{2}} , \qquad (8)$$

which is the same discriminability index used by some detection theorists (e.g., Luce, 1963). Log d is also monotonically related to d′, the discriminability index obtained when z, rather than log, data transforms are used (e.g., Green & Swets, 1974).

Role of reinforcement
in signal-detection theory

In schedule-control research, the relative frequency of reinforcement has often been identified as a major factor in the control of behaviour (e.g., de Villiers, 1977). In signal-detection theory, the relative frequency of a particular stimulus (stimulus-presentation probability, or SPP) has likewise been shown to control behaviour (e.g., Clopton, 1972; Elsmore, 1972; Galanter & Holman, 1967; Hume & Irwin, 1974; Markowitz & Swets, 1967; Schulman & Greenberg, 1970; Terman & Terman, 1972). However, Equations 2 and 3 above are silent on the role of stimulus-presentation probability.

Variation in SPP is said to alter the criterion (response bias) of the subject. However, if S1 is presented on 90% of trials

and S2 on only 10% of trials (SPP = .9), the subject may obtain 90% of the reinforcers for a P1 response. Variations in SPP have, therefore, been confounded with variations in the obtained reinforcement ratio. One of our first experiments was concerned with the manipulation of both SPP and relative-reinforcement rate to determine which of these two variables was effectively controlling behaviour in the detection task.

Six pigeons were trained to discriminate two different intensities of white light (S1 = 33 cd/m²; S2 = 7 cd/m²) displayed on the center key of a three-key operant chamber under three experimental procedures. Following presentation of either S1 or S2 on the center key, a peck on the center key turned on the two side keys which were illuminated red (left) and green (right). Correct responses were left-key pecks following S1 presentations, and right-key pecks following S2 presentations.

In the first procedure, SPP was varied from .1 to .9, in steps of .2. Food reinforcement for correct side-key responses was arranged on a single variable-ratio schedule, and unreinforced correct responses were followed by a 3-sec magazine light. Errors (left after S2, right after S1) were followed by 3 sec blackout. With such probabilistic scheduling, the obtained reinforcement ratio, Rw/Rz, covaried with the ratio of the frequencies of stimulus presentation, and with the subject's behaviour. This is an uncontrolled reinforcement-ratio procedure (McCarthy & Davison, 1980a), and it is typical of most signal-detection research.

In the second procedure, reinforcement for correct left- and right-key responses was held constant by arranging equal, nonindependent (Stubbs, 1976; Stubbs & Pliskoff, 1969) concurrent variable-interval variable-interval (VI VI) schedules and SPP alone was varied from .1 to .9, in steps of .2. Finally, in the third procedure, SPP was held constant, and the ratio of reinforcements obtained for correct responses was varied by changing the concurrent VI VI schedules. These last two procedures are called controlled reinforcement-ratio procedures (McCarthy & Davison, 1980a) because the reinforcement ratio in a particular condition is set and

cannot covary with either response ratios or SPP.

When the reinforcement ratio either covaried with SPP (Procedure 1), or was directly varied with SPP constant (Procedure 3), the data fitted nicely to Equations 2 and 3. In both these procedures, response bias estimates (Equation 6) showed statistically significant trends across conditions. However, when SPP alone was varied with a controlled unit reinforcement ratio (Procedure 2), behaviour failed to change with SPP, and no trends in response bias were found. Estimates of stimulus discriminability (Equation 8), as expected, showed no trends in any of the procedures, and were not significantly different between the three procedures.

We concluded, therefore, that stimulus-presentation probability alone was not an effective biaser in the detection task. Rather, its apparent biasing effect arises from changes in the obtained reinforcement ratio for the two correct responses. For example, if S1 is presented more frequently than S2, correct responses emitted after S1 presentations will be reinforced more frequently than correct responses emitted after S2 presentations. Thus, variation in SPP directly causes variation in the obtained reinforcement ratio. It is these relative-reinforcement frequency changes which bias choice behaviour in signal detection. Clearly, then, SPP need not be shown as an independent variable in the behavioural models of signal detection. Our research has also suggested that other variables known to affect concurrent-schedule choice can also be used to bias detection performance, e.g., reinforcement magnitudes (Boldero, 1978), delays and qualities (de Villiers, 1977), and response requirements (Beautrais & Davison, 1977; Davison & Ferguson, 1978).

Having established that obtained relative rate of reinforcement, and not stimulus-presentation probability, is the effective biaser in detection experiments, we then showed that a constant measure of response bias (*iso*bias) can only reliably be obtained from a procedure which controls the obtained reinforcement ratio (McCarthy & Davison, 1980a; in press). As described above, a controlled reinforcement-ratio procedure is one in which reinforcers are scheduled such that the relative-reinforcement rate is fixed at a particular value which cannot be affected by changes in the distribution of responses (Stubbs, 1976). In most detection experiments, however, reinforcements are typically arranged to follow each correct response (e.g., Hume & Irwin, 1974), or to follow correct responses in a probabilistic fashion, with all correct responses contributing to the same variable-ratio schedule (e.g., Elsmore, 1972; Hobson, 1978). This is an uncontrolled reinforcement-ratio procedure which allows the number of reinforcements obtained for left- and right-key responses to vary with the animal's behaviour, and *alloio*bias (varying or differing bias; McCarthy & Davison, 1980a; in press) results. Alloiobias can, however, be measured (but not predicted) within the framework provided by our behavioural models.

In addition, we have found that the relation between traditional detection-theory measures of bias (e.g., ß opt; Hume & Irwin, 1974), and the relative number of obtained reinforcements for left- and right-key responses parallels the relation between response and reinforcement allocation in concurrent VI VI schedules (McCarthy, 1979; McCarthy & Davison, in press).

Having established control of behaviour in the detection task by the *relative* rate of occurrence of reinforcement, we then investigated the effects on detection performance of *absolute* overall reinforcement rate. In concurrent-schedule research, preference (or, allocation of responses between the two alternatives) is independent of absolute-reinforcement rate (Fantino, Squires, Delbruck & Peterson, 1972). Using a standard yes-no detection task, we trained pigeons to detect differences in stimulus duration under three levels of absolute reinforcement rate (McCarthy & Davison, Note 2). Two red stimuli, differing in duration, were arranged probabilitistically on the center key of a three-key operant chamber. On completion of the center-key duration, the center-key light was extinguished, and the two side keys were illuminated white. A left-key response was correct when the shorter stimulus had been

in effect, and a right-key response was correct when the longer stimulus had been in effect.

In the first procedure, every correct response produced food reinforcement. In the second and third procedures, food reinforcement was delivered for correct responses according to a VI 45-sec schedule and a VI 15-sec schedule, respectively. We found both stimulus discriminability and response bias to be independent of absolute reinforcement rate, thus generalizing to a signal-detection procedure Fantino et al.'s (1972) finding that overall-reinforcement rate has no effect on response distribution in choice.

Taken together, the above results underline the importance of arranging explicit reinforcement contingencies in studies of signal detection. In our detection experiments, the behaviour of the animals is maintained explicitly through reinforcement and, thus, reinforcement variables are clearly specified and arranged adequately to maintain detection performance. In the absence of reinforcement, detection performance ceases. More than this, differential reinforcement is required to maintain performance (Davison & McCarthy, 1980). However, most research in contemporary psychophysics has placed primary emphasis upon the sensory performance of human subjects. As a result, less effort has been expended in understanding the role played by reinforcement. Insufficient attention has been given to specifying the actual reinforcers involved, and such reinforcers (e.g., money, points, etc.) are often delivered *non*-contingently as a means simply of providing and maintaining behaviour. While the differential reinforcers reside in the instructions, such instructions are a rather ill-defined reinforcement variable (McCarthy & Davison, 1979; in press).

Any general description of detection performance must give proper consideration to the role played by reinforcement. The present model provides such an account. It relates the signal-detection paradigm to concurrent schedules of reinforcement, and yields orderly, quantitative data relating detection performance to the conditions of reinforcement. The theory of signal detection has, on the other hand, suc-cessfully quantified stimulus effects, and attempts to relate stimulus parameters to the physical properties of the stimuli are well documented. We now turn our attention to the question: How adequately does the present behavioural model account for stimulus effects in studies of schedule control?

Measurement of stimulus effects in schedule-control research

The possibility of unifying stimulus and reinforcement effects within a single theoretical framework is further enhanced by the generalization of our behavioural model of signal-detection performance to the equivalent free-operant paradigm. At this point, however, a new concept must be introduced.

Reinforcing errors in signal-detection experiments

Typically, in detection experiments, errors (i.e., misses and false alarms) have no consequence or are punished in some way (e.g., time out with animals, Hume, 1974). However, from a behavioural point of view, the effects of arranging reinforcement for errors are just as informative as the effects of reinforcing correct responses. With the introduction of reinforcement in the normally-empty cells of the payoff matrix (Cells X and Y, Figure 1), the standard signal-detection discrete-trial paradigm becomes a special case of a more general free-operant design in which two multiple schedules, each associated with a distinct discriminative stimulus, are available on one key concurrently with a common schedule of reinforcement on a second key (i.e., a multiple-concurrent schedule; Pliskoff, Shull & Gollub, 1968). Such an arrangement permits the quanti-fication of stimulus effects in schedule-control research in a manner analogous to that of the detection procedure. Apart from the benefits of such a general measure of discriminability, it allows choice behaviour in both the discrete-trial detection task, and the free-operant schedule-control experiment, to be predicted.

The pioneering work on the effects of reinforcing errors was carried out by Nevin and his coworkers (Nevin, 1970; Nevin, Olson, Mandell & Yarensky, 1975; Nevin

et al., Note 1). Some interesting results emerged. For example, detection theorists assume discriminability to depend solely upon stimulus variables and, thus, to be independent of payoff (Green & Swets, 1974). However, Nevin et al. (1975) and Nevin et al. (Note 1) showed that, as error-reinforcement probability is increased, so traditional measures of discriminability (e.g., A′; Grier, 1971) fall. Such observations led in turn to the development of behavioural models for detection performance which encompassed both the usual detection paradigm in which only correct responses are reinforced (the standard procedure, Figure 1), and the situation in which reinforcement is scheduled for error responses (the reinforcement-for-errors procedure). One such model was proposed by Davison and McCarthy (1980)[2].

Firstly, as in the Davison and Tustin (1978) no-error reinforcement model, overall allocation of choice responses to the alternatives will be determined by the reinforcements obtained for the two responses. In the reinforcement-for-errors procedure, however, this reinforcement ratio will comprise all reinforcers, and behaviour will follow this reinforcement ratio with a certain sensitivity, a (Baum, 1974). While we assume that discriminability, log d (the maximal ability of a subject to tell two stimuli apart) remains constant when errors are reinforced, Nevin and his colleagues reported that conventionally-measured discriminability shown by the subject decreased when errors were reinforced. Thus, we make the additional assumption that the degree of discrimination which can be shown in the reinforcement-for-errors paradigm is a function of both the discriminability of the stimuli (log d), and the degree of association between reinforcers and stimulus presentations. Discrimination, as distinct from discriminability, is thus given by:

$$Discrimination = \left(\frac{Rc - Re}{Rc + Re}\right) \cdot \log d ,$$

where Rc is the number of reinforcements obtained for correct responses (Rw + Rz in Figure 1), and Re is the number of reinforcements obtained for errors (Rx + Ry in Figure 1). In other words, dis-

crimination will be degraded by reinforcing errors.

Our full reinforcement-for-errors model is thus:
Following S1 presentations,

$$\log \left(\frac{Pw}{Px}\right) = a \log \left(\frac{Rw + Ry}{Rx + Rz}\right)$$

$$+ \left(\frac{Rc - Re}{Rc + Re}\right) \log d + \log c , \qquad (9)$$

and, following S2 presentation,

$$\log \left(\frac{Py}{Pz}\right) = a \log \left(\frac{Rw + Ry}{Rx + Rz}\right)$$

$$- \left(\frac{Rc - Re}{Rc + Re}\right) \log d + \log c . \qquad (10)$$

When the association between reinforcement and stimulus presentations is 1.0 (i.e., only correct responses are reinforced), Equations 9 and 10 simplify to Equations 2 and 3 of the no-error reinforcement model. When the association is -1.0, only errors are reinforced, and the equations again simplify to the Davison and Tustin (1978) model. When, however, the association is zero, no discrimination between S1 and S2 is shown, and both response ratios are a function only of the obtained reinforcement ratio. Discriminability (log d) cannot, therefore, be measured in the absence of the association of reinforcement and stimulus presentations.

Adding Equations 9 and 10 gives the equivalent of a bias function:

$$\log \left(\frac{Pw}{Px}\right) + \log \left(\frac{Py}{Pz}\right)$$

$$= 2a \log \left(\frac{Rw + Ry}{Rx + Rz}\right) + 2 \log c , \qquad (11)$$

and, subtracting Equation 10 from Equation

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[2] Nevin, Jenkins, Whittaker & Yarensky (Note 1) proposed a model similar to that reviewed here. Their model, which assumes unit reinforcement sensitivity (a = 1) and no inherent bias (c = 1), is a special case of our model. The relative merits of the two models, and the necessity for the generalized model, are discussed in Davison and McCarthy (1980).

9 gives the equivalent of a stimulus function:

$$\log\left(\frac{P_w}{P_x}\right) - \log\left(\frac{P_y}{P_z}\right)$$

$$= 2\left(\frac{R_c - R_e}{R_c + R_e}\right) \log d . \qquad (12)$$

Equation 12 shows correctly that conventional discriminability estimates (Equation 8) are only independent of payoff when no error reinforcement is obtained. More generally, then, the conventional discriminability-measurement procedure assesses discrimination. It measure discriminability only when error reinforcement is absent.

To test the effectiveness of our reinforcement-for-errors model, we trained pigeons to discriminate between two durations of a white center-key light. Following presentation of a 5-sec light, left-key pecks were correct, and following presentations of a 10-sec light, right-key pecks were correct. All correct responses produced 3-sec access to wheat with a probability of .7. The probability of food reinforcement for errors (left after long, right after short) was increased from 0 to .9, in steps of .1, in successive experimental conditions. Analysis of the data according to Equations 9 and 10 gave parameter estimates (reinforcement sensitivity, discriminability, and inherent bias) with small standard devations, and a large percentage of the data variance was accounted for (see Davison & McCarthy, 1980 for a more detailed account of these results).

In addition, we reanalysed data from two other reinforcement-for-errors experiments (Nevin et al., 1975; Nevin et al., Note 1), and, again, our model provided a convincing fit to the data (see Davison and McCarthy, 1980).

Nevin (personal communication, 1980) has pointed out that the phi coefficient (a nonparametric measure of association in 2×2 matrices) could be used to modify log d rather than the stimulus-reinforcement association measure used here. Our data analyses have shown that the phi coefficient is as good as our measure and may, in fact, explain behaviour better in certain situations where the reinforcements obtained are asymmetrically distributed in the cells of the detection matrix (Figure 1).

The analyses of these three sets of data on reinforcing errors in a signal-detection paradigm, covering both controlled and uncontrolled reinforcement-ratio procedures and two different species of subject (rats and pigeons), extends the behavioural account of detection performance to the more general free-operant paradigm. More importantly, measures of stimulus discriminability are, for the first time, available in the free-operant situation.

Stimulus measures from schedule-control data

Multiple-concurrent schedules (Pliskoff et al., 1968), as noted above, have the same matrix of events as a reinforcement-for-errors detection procedure, with the exception that the former arrangement is a free-operant procedure, while the latter employs discrete trials. We analysed two sets of multiple-concurrent schedule data (Lobb & Davison, 1977; Nevin, Mandell & Whittaker, 1978) from which stimulus discriminability measures had not previously been obtained. Analysis according to Equations 9 and 10 again yielded precise parameter estimates (see Davison & McCarthy, 1980). In addition, we showed time-allocation data (White, 1978) to be a useful way of obtaining stimulus-discriminability measures in multiple schedules.

We are currently investigating how our measures of discriminability in these free-operant experiments, where control by reinforcement schedules is of primary concern, compare with discriminability measures obtained from the detection experiment in which most emphasis is placed upon stimulus control (McCarthy, Davison & Jenkins, Note 3). Six pigeons were trained to detect differences in light intensity under four experimental procedures. The first two procedures were multiple-concurrent procedures in which the components were changed randomly after each reinforcement. Two dull stimuli (Component 1) or two bright stimuli (Component 2) were randomly presented on left and right keys according to set probabilities. The birds were required to peck the left key if the dull pair was

presented, and the right key if the bright pair was presented. In Procedure 1, correct left- and right-key responses were reinforced according to two nonindependent VI 60-sec schedules, and incorrect responses (left-key pecks during Component 2, right-key pecks during Component 1) had no consequence. Procedure 1 was thus a multiple (concurrent VI 60-sec extinction) (concurrent extinction VI 60-sec) schedule. In Procedure 2, food reinforcement was arranged for every correct left- and right-key response, and incorrect responses produced 3 sec blackout. The second procedure was thus a multiple (concurrent fixed-ratio 1 extinction) (concurrent extinction fixed-ratio 1) schedule. In both these two procedures, each component terminated in reinforcement. At this point, the probability generator was sampled, and a new trial (presentation of Component 1 or Component 2) began. Stimulus-presentation probability (or, the probability of occurrence of the bright stimulus pair, Component 2) was varied from .1 to .9 in steps of .2 over five experimental conditions.

Stimulus discriminability measures obtained from these two procedures were compared with measures obtained from a third procedure—an analogue of the standard yes-no detection task. Initially, the two keys were lit green. A peck on either the left or right key extinguished the two green key lights, and produced, for 3 sec, either two dull (S1) or two bright (S2) key lights, the intensities of which were identical to those of Procedures 1 and 2. Following the 3-sec stimulus presentation, the white lights were extinguished, and the two keys were lit red. Every correct response (left after dull, right after bright) produced 3-sec access to wheat, and incorrect responses (left after bright, right after dull) produced 3-sec blackout. Under this procedure, stimulus-presentation probability (or, the probability of occurrence of the dull stimulus pair, S1) was varied from .1 to .9 in steps of .2 across five experimental conditions.

Initial results showed no significant difference between discriminability estimates for Procedures 1 and 2, but stimulus discriminability was significantly *lower* in the signal-detection procedure than in the

multiple-concurrent free-operant procedures. The implication is, then, that the standard yes-no detection task may not accurately assess the asymptotic ability of an animal to discriminate. One reason for this could be the fact that in the signal-detection procedure, unlike the multiple-concurrent schedule procedure, the stimuli are not present when the choice is made. Rather, there is a small temporal delay between presentation of the stimuli and the choice response.

To test this suggestion, we ran a fourth procedure which was identical to the signal-detection procedure except that the two bright or two dull key lights remained on until the birds had reported the stimulus. This modification yielded discriminability measures significantly higher than those obtained from the standard detection procedure, and not significantly different from discriminability estimates obtained from the first two multiple-concurrent procedures. It appears, then, that the common ground between discrete-trial signal-detection procedures, and the free-operant schedule-control experiments is provided by the random-component multiple-concurrent schedule with components terminating in reinforcement (Procedures 1 and 2 above).

Conclusions and New Directions

The research reviewed here provides empirical support for a model of behaviour capturing both stimulus and reinforcement variables within a single theoretical framework. It allows for the quantification of stimulus effects in free-operant paradigms, and a better understanding of reinforcement effects in studies of signal detection.

At the same time, a large number of other areas of application are suggested. In this laboratory, for example, we are currently generating detailed isobias and alloiobias contours under both controlled and uncontrolled reinforcement-ratio procedures in an attempt to clarify the nature of, and the conditions which produce, empirical isobias contours. In the detection-theory literature, there appears to be no generally-accepted way of measuring bias and, hence, there is little agreement on the true shape of empirical iso- (equal-) bias

contours. However, many of the problems that detection theorists have had with bias have been due to a very large extent to the inadequate specification of the variables which lead to bias. This experiment, it is hoped, will clarify these problems.

In addition, we are working on a better understanding of the effects of nonsensory variables on thresholds to stimulation and sensitivity to stimulus differences. Two experiments are in progress which employ pigeons as subjects, and light intensity as the stimulus dimension. These two experiments are designed to investigate the effects of controlled and uncontrolled reinforcement-ratio procedures on absolute-threshold measures, the values of differential thresholds determined by a signal-detection method over a particular intensity range, and the effect on the estimate of differential-threshold value of controlling the subject's response bias. We have found that response bias may vary widely close to threshold.

Initial findings have resulted in the derivation of the psychometric function from the stimulus equation (Equation 7) of the Davison and Tustin (1978) model. This derivation allows thresholds, in addition to stimulus discriminability (log d) and reinforcement, to be incorporated into a model of behaviour which can be applied to data obtained from classical and contemporary psychophysical experiments, and from schedule-control studies.

Peter Jenkins[3] has been analysing the effects of reinforcement delays of up to 30 seconds following the choice response in a detection task. While stimulus discriminability appears to decrease with increasing delay, response bias, on the other hand, tends to become more extreme.

Both Jenkins (Auckland University) and Mandell (Lowell University, U.S.A.) have, independently, been investigating the discriminability of schedules of reinforcement but, sadly, they appear to have found incompatible results. While Mandell's birds could discriminate different reinforcement rates on concurrent schedules (Mandell, personal communication, 1980), Jenkins' birds were unable to do so, even though

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[3] Post-Doctoral Fellow from University of New Hampshire, U.S.A., 1979-1980.

behavioural control by the concurrent schedules was excellent. Clearly, there are many variables operating here which we do not, as yet, fully understand.

Another interesting application of the present research is that made by McKenzie and White (Note 4). They reported an extension of the Davison and Tustin (1978) model for the situation in which temporal delays were interpolated between presentation of the stimuli in a detection task, and the availability of the choice responses. They argued that the effect of the delay, in what was essentially a recall procedure, was to degrade discriminability according to an exponential function of time. That is, the delay decremented discriminability (log d) as follows:

Following S1 presentations,

$$\log \left(\frac{Pw}{Px} \right) = a \log \left(\frac{Rw}{Rz} \right)$$
$$+ (1 - bt)\log d + \log c ,$$

and, following S2 presentations,

$$\log \left(\frac{Py}{Pz} \right) = a \log \left(\frac{Rw}{Rz} \right)$$
$$- (1 - bt)\log d + \log c ,$$

where t is the delay, and b is a time constant.

Unfortunately, this model predicts a *reversal* of choice at long delays. Research currently in progress in this laboratory is designed to test a different version which assumes that the function relating discriminability to time is a rectangular hyperbola. Following S1 presentations,

$$\log \left(\frac{Pw}{Px} \right) = a \log \left(\frac{Rw}{Rz} \right)$$
$$+ \left(\frac{b}{b+t} \right)\log d + \log c ,$$

and, following S2 presentations,

$$\log \left(\frac{Py}{Pz} \right) = a \log \left(\frac{Rw}{Rz} \right)$$
$$- \left(\frac{b}{b+t} \right)\log d + \log c .$$

Each of the areas discussed above constitutes a new and exciting extension of our attempts to relate quantitatively areas of Psychology which have hitherto remained disparate. Together, they lead to a more complete understanding of behaviour in a diversity of paradigms.

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